The need for carbon emissions-driven climate projections in CMIP7

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Abstract. Previous phases of the Coupled Model Intercomparison Project (CMIP) have primarily focused on simulations driven by atmospheric concentrations of greenhouse gases (GHGs), both for idealized model experiments, and for climate projections of different emissions scenarios. We argue that although this approach was pragmatic to allow parallel development of Earth System Model simulations and detailed socioeconomic futures, carbon cycle uncertainty as represented by diverse, process-resolving Earth System Models (ESMs) is not manifested in the scenario outcomes, thus omitting a dominant source of uncertainty in meeting the Paris Agreement. Mitigation policy is defined in terms of human activity (including emissions), with strategies varying in their timing of net-zero emissions, the balance of mitigation effort between short-lived and long-lived climate forcers, their reliance on land use strategy and the extent and timing of carbon removals. To

explore the response to these drivers, ESMs need to explicitly represent complete cycles of major GHGs, including natural processes and anthropogenic influences. Carbon removal and sequestration strategies, which rely on proposed human management of natural systems, are currently calculated in IAMs during scenario development with only the net carbon emissions passed to the ESM. However, proper accounting of the coupled system impacts of and feedback on such interventions requires explicit process representation in ESMs to build self-consistent physical representations of their potential effectiveness and risks under climate change. We propose that CMIP7 efforts prioritize simulations driven by CO_2 emissions from fossil fuel use, projected deployment of carbon dioxide removal technologies, as well as land use and management, using the process resolution allowed by state-of-the-art ESMs to resolve carbon-climate feedbacks. Post-CMIP7 ambitions should aim to incorporate modeling of non-CO_2 GHGs (in particular, sources and sinks of methane and nitrous oxide) and process-based representation of carbon removal options. These developments will allow three primary benefits: (1) resources to be allocated to policy-relevant climate projections and better real-time information related to the detectability and verification of emissions reductions and their relationship to expected near-term climate impacts (2) scenario modeling of the range of possible future climate states including Earth system processes and feedbacks which are increasingly well-represented in ESMs and (3) optimal utilization of the strengths of ESMs in the wider context of climate modeling infrastructure (which includes simple climate models, machine learning approaches and km-scale climate models).

1 Introduction

Past phases of the Coupled Model Intercomparison Project (CMIP)(Meehl et al., 2007; Taylor et al., 2012; Eyring et al., 2016) have been the principal source of process-based climate and Earth system modeling outcomes for IPCC Assessment Reports (Intergovernmental Panel on Climate Change, 2023). The vast majority of CMIP experiments have considered boundary conditions where concentrations of greenhouse gases are prescribed, both in the implementation of idealized simulations and in future scenarios which inform climate policy (O'Neill et al., 2016; Arnell et al., 2004; van Vuuren et al., 2011; Gillett et al., 2016).

In the two most recent IPCC cycles, scenario experiments have been defined in terms of Representative Concentration Pathways, or RCPs (Moss et al., 2010), which define futures in terms of approximate end-of-century radiative forcing levels to provide a set of consistent scenarios to be used in climate research, and to provide multiple model-informed climate impact assessments at different warming levels. In ScenarioMIP/CMIP6, scenarios were defined in terms of SSPs representing broad socioeconomic background states combined with global mean end-of-century radiative forcing targets (O'Neill et al., 2016; Riahi et al., 2017). IPCC AR6 (Intergovernmental Panel on Climate Change, 2023) adopted the notation of SSPX-Y, where X is one of 5 SSPs, and Y is the radiative forcing level used in the creation of scenarios for ScenarioMIP.

The SSP design is concentration-driven, with scenarios defined by their climate response. For example, SSP1-2.6 is a scenario which is designed to achieve a radiative forcing of 2.6 Wm^{-2} in 2100. This is achieved by linking the Integrated Assessment

Model (IAM) with a simple climate model (SCM), to solve for a desired climate outcome (Riahi et al., 2017). To meet the predefined climate target, the IAM-SCM integration is iteratively solved with either carbon emissions constraints or carbon price trajectories until the climate target is met with sufficient accuracy (Calvin et al., 2019; van Vuuren et al., 2015; Baumstark et al., 2021). For the SSP design, all IAMs used the same simple climate model (MAGICC6.8) to ensure they reached the same forcing level in 2100 (Riahi et al 2017). In the CMIP pipeline, the resulting emissions from each IAM SSP scenario are harmonized to a common historical dataset, any missing emissions infilled(Kikstra et al., 2022; Gidden et al., 2019), and then multi-gas concentration pathways are estimated by a common SCM (Meinshausen et al., 2020), to be used as boundary conditions for ESM simulations in future scenario projections, together with pre-computed spatial information on land use and aerosol emissions (Feng et al., 2020; Hurtt et al., 2020).

Like the CMIP5-era RCPs which predated them (Moss et al., 2010), the SSPs use concentrations as a definitional anchor point. In this framework, Earth System uncertainties as a function of concentrations are estimated by climate models (in practice, by the CMIP ensemble, Figure 1). This has pragmatic advantages in terms of coordinating research across climate disciplines, but excludes uncertainties arising from feedbacks from the carbon cycle back onto atmospheric CO_2. The concentration-based framework has no structurally consistent mechanism for representing these uncertainties in a process-resolving fashion - the IPCC AR6 WG1 report relied on emulators which were informed indirectly by CMIP models, where climate and carbon uncertainties were independently calibrated [see cross chapter box 7.1 in (Forster et al., 2023)]. In some cases, climate assessments bypass the causality chain and express impacts as a function of global mean temperatures (Figure 1 and cross-chapter box 7.1 in (Forster et al., 2023)].)

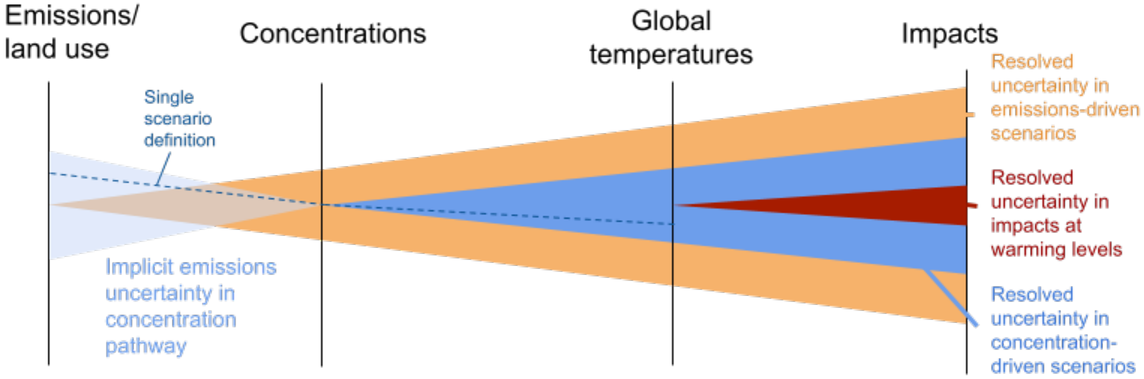

Figure 1: A conceptual illustration (in the style of (Pfleiderer et al., 2023)**) of the propagation of uncertainty using concentration and emissions-based anchor points**

To date, CMIP phases have primarily represented anthropogenic emissions as a residual in concentration-driven simulations (Friedlingstein et al., 2006; Jones et al., 2016), thereby computing compatible carbon emissions consistent with the prescribed concentrations. This is achieved by assessing the residual flux of carbon which would be necessary to balance the internal carbon budget of an ESM simulation which is run in concentration-driven mode. However, in scenarios there are often significant differences between the carbon cycle representations in the original IAM structure and the ESM, such that the compatible emissions are conceptually distinct from the original scenario design (Koven et al., 2022) (and Figure 2). For ambitious mitigation scenarios such as SSP1-1.9, these differences account for a significant variation in the total cumulative emissions consistent with the prescribed concentration pathway (post-2014 cumulative emissions before net zero in SSP1-19 range from 200 to 280GtC, see Figure A1) As the scenario literature increasingly focuses on mitigation strategy relevant to the Paris agreement (Rogelj et al., 2019; Sognnaes et al., 2021), it becomes increasingly necessary for ESM simulations to accurately represent both historical emissions and the outcomes of emissions scenarios which are consistent with the socioeconomic trajectories they are meant to represent.

A second issue with compatible emissions is the model-dependent ambiguity in their computation. Because compatible emissions are computed as a residual, after accounting for carbon in the land surface, ocean and atmosphere, it is necessary that all models output the needed fields to account for the complete carbon budget. However, CMIP6 models remain inconsistent in their outputting, unit conventions and definitions of component-level carbon fluxes, which complicate analysis. Such issues must be better addressed in emissions-driven simulations where reconstruction of the carbon budget is of first order importance to understanding the model response. In addition, there is inconsistency in the carbon pools and land use processes represented in different models - confusing the interpretation of the compatible emissions (Liddicoat et al., 2021). Furthermore, compatible emissions can only diagnose the fossil-fuel component (Jones et al., 2013). This meant for example that IPCC AR6 had to mix ESM output for diagnosed fossil fuel emissions and IAM-based scenario data on land-use emissions in creating synthesis figures such as WG1-SPM.7.

In addition, ESMs calculate land use, land use change and forestry (LULUCF) emissions dynamically based on the changing land-use patterns which can markedly differ from the original LULUCF fluxes computed in IAMs (Quesada et al., 2018; Wilkenskjeld et al., 2014), and these differences are manifested in the compatible emissions which, in theory, should represent fossil fuel emissions. This also means that compatible emissions calculated in SCMs are not comparable with ESM estimates, because aggregate LULUCF emissions are exogenously prescribed in most SCMs - creating discrepancies between SCM and ESM estimates of remaining carbon budgets for given warming levels (Millar et al., 2017).

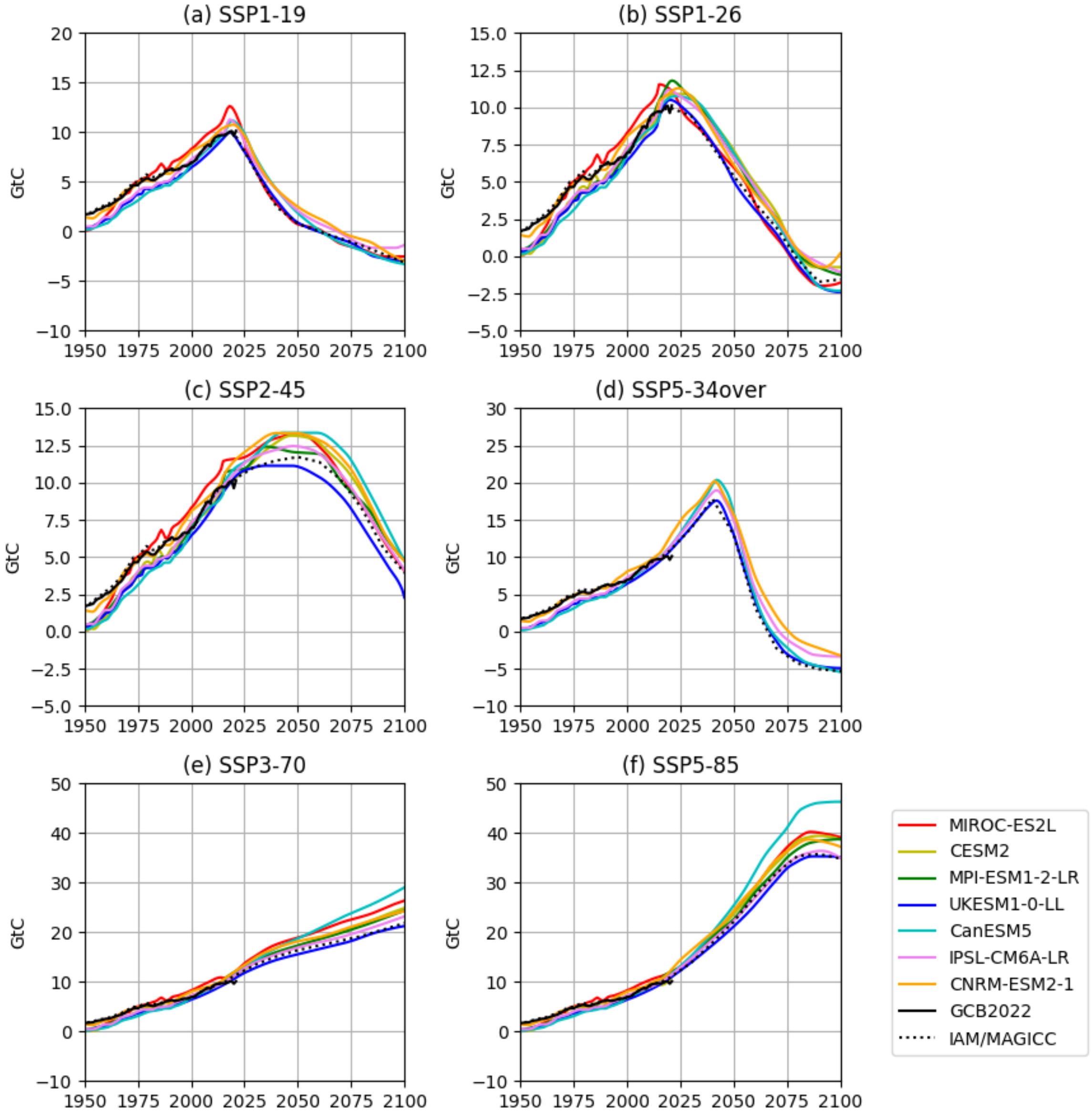

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Figure 2: Compatible fossil emissions for a range of scenarios and Earth System Models in CMIP6, showing MAGICC calculated CO2 emissions from IAM scenarios (Meinshausen et al., 2020) **(dotted black), and the compatible fossil emissions in CMIP6 ScenarioMIP simulations (colored lines). Historical fossil emissions from the global carbon project (GCB2022** (Friedlingstein et al., 2022b)**) are shown for context.**

130 Assessing compatible emissions for CMIP6 scenarios underlines that there are significant differences in the simulated compatible emissions amongst ESMs (Figure 2). For example, in the concentration driven SSP1-2.6 scenario in CMIP6, ESM-simulated net-zero dates measured in terms of compatible fossil fuel emissions ranged from 2076-2086, compared with the IAM estimate of 2076 (Gidden et al., 2019; van Vuuren et al., 2017) (Figure 2). The fact that the IAM/MAGICC trajectory lies on the edge of the ESM compatible emissions distribution is worthy of further consideration, either indicating that

MAGICC carbon-climate dynamics are a slight outlier amongst the ESMs, or a methodological difference between the compatible emissions in the ESMs and the harmonized emissions trajectory produced in the IAM/MAGICC pipeline (Meinshausen et al., 2020). Differences between compatible emissions are also evident in the historical period, slightly exceeding the historical uncertainty in emissions. For example, 2014 compatible carbon fossil fuel emissions span from 9.1 to 10.9 GtC in CMIP6 concentration driven models (Figure 2), compared with historical estimate of 9.7±0.5 GtC (Friedlingstein et al., 2022b).

The only emissions-driven scenarios in CMIP6 took place as part of C4MIP (Jones et al., 2016) , repeating high emissions scenarios (*esm-SSP5-8.5*) and an extreme overshoot scenario (*esm-SSP5-3.4-over*) with a small subset of models. Notably, these scenarios were chosen to inform assessments of carbon feedbacks under high emissions (but they are not themselves considered to represent realistic near-term futures (Hausfather and Peters, 2020b)). As a result, multi-model ESM results from the CMIP6 scenario effort as presented in IPCC-AR6-WG1 (e.g. AR6-WG1-Fig4.11) exclude an assessment of carbon cycle uncertainty (Tebaldi et al., 2021; IPCC 2021 WG1 Chapter 4). Where carbon-climate feedbacks were considered in IPCC consideration of SSP projections (e.g. AR6-WG1-Fig4.35), this was achieved by probabilistic SCM ensembles informed by idealized ESM experiments to inform carbon feedback parameter uncertainty (Arora et al., 2020; Masson-Delmotte et al., 2023).

In this perspective, we argue that the increasing sophistication and stability of emissions-driven model configurations relevant for modelling greenhouse gas cycles means that this approach can now be reassessed. The urgent need for process-based information on the mitigation effectiveness of fossil fuel emission reductions, carbon dioxide removal, and land use policies, requires a framework for the increased inclusion of emissions-driven experiments in upcoming CMIP cycles, in the presence of heterogeneous model complexity, timeline constraints and technological challenges.

These dimensions increasingly dominate many of the most pressing questions in climate policy, and process resolving ESMs are in a unique position to provide self-consistent assessments of climate policies which have both regional, temporal, and species dimensions. Constructing scenarios which fully explore these dimensions requires scenario definitions which go beyond end-of-century forcing or temperature level implied in a concentration pathway. Rather, mitigation strategy needs to be defined in terms of activity and consequence: where human activities include fossil fuel and other industrial emissions, combined with regionally resolved descriptions of land use change and management.

The ‘hybrid’ approach proposed in this study considers a set of headline experiments in CMIP7 which are preferentially driven by carbon and aerosol emissions, with prescribed values for other atmospheric components. And, for those models capable, dedicated activities to assess process-resolving carbon removal activities, plus the coupled dynamical response of the Earth System to non-CO_2 gases such as N_2O and CH_4 would provide critical groundwork for their eventual representation in following CMIP activities.

2 The need for emissions-driven ESM scenarios

Climate policy is framed in terms of emissions - naturally focussing on the elements that can inform mitigation decisions, such as emission benchmarks, carbon budgets and the timing of net-zero. In addition, emissions-driven climate metrics (Arora et al., 2020) such as the transient climate response to cumulative emissions of carbon dioxide (TCRE, (Allen et al., 2009; Jones and Friedlingstein, 2020; Matthews et al., 2009) and the Zero Emissions Commitment (ZEC, (Jones et al., 2019) are important and policy-relevant summary quantifications of the Earth System response to climate mitigation efforts. As of today, countries have committed to achieving climate targets, including net-zero targets, under the Paris Agreement, that constrain the future emissions space. Consistency of simulations with policy constraints is key to providing policy relevant information.

However, the dominance of concentration-driven scenarios means that CMIP6 does not contain self-consistent simulations of mitigation strategy and their climate outcome in Earth System Models. As a result, though IAM simulations already frame scenarios in terms of emissions pathways (Sognnaes et al., 2021), the simplified internal representation of climate and carbon processes does not allow for a comprehensive assessment of the underlying carbon cycle uncertainties associated with the scenario tradeoffs, generally relying on simple climate models to represent uncertainty in carbon-climate feedbacks (Nauels et al., 2017; Bodman et al., 2016; Damon Matthews et al., 2021; Watson-Parris and Smith, 2022), where idealized ESM results may be indirectly used in the calibration of the simple climate model parameter distributions.

Simple climate models are well suited to this application – with sufficient structural complexity to emulate more complex models, but sufficiently computationally lightweight to allow rapid sampling of a relatively low parameter space to find model variants which are consistent with observations (Smith et al., 2024; Meinshausen et al., 2011). The increasing use of simple climate models in assessment (Nicholls et al., 2022) as the primary mechanism for representing uncertainty in global scale climate response allows Earth System Model simulations in CMIP to focus on coupled complex process representation. A CMIP ensemble with a primary focus on emissions-driven scenarios, starting with CO_2 emissions in CMIP7 but with a longer term objective to represent human activity through diverse emissions or land management, would allow ESM scenarios to represent real-world climate policy and its outcomes. As emissions and activity-driven processes are improved in ESMs, it is essential that SCMs can emulate any new emergent global coupled dynamics which arise in the ESMs (e.g. nonlinear behavior or tipping points). In short, the presence of a larger model ecosystem including ESMs, SCMs and km-scale models allows for each model class to excel in dimensions which are suited to the platform. For ESMs, the computational efficiency and resolution must balance the need to represent coupled complex processes with the need to be able to calibrate and spin up the coupled system.

2.1 Key science needs for emissions-driven models

This emission-driven CMIP7 strategy would enable four key scientific benefits, which we outline in this section: 1) process-resolved assessment of carbon removal assumptions which underpin the capacity for climate temperature overshoot, 2) trade-offs between fossil fuel emissions, carbon removals, land use change, and short lived climate forcers on regional scales including relevant feedbacks, 3) integrated process-resolution of system thresholds, nonlinearities, and risks which might exacerbate climate impacts and modify Earth System feedbacks in warmer climates and 4) relevant simulations to inform the verification of mitigation activity.

Activity-driven representation of carbon removal

The plausibility and effectiveness of the gigatonne-scale carbon dioxide removal implied by mid- to high-mitigation scenarios is a key uncertainty (Marcucci et al., 2019) for end-of-century warming outcomes, given that the majority of the world's economy has pledged net-zero CO_2 or GHG targets which are themselves conditional on significant amounts of carbon dioxide removal (Grant et al., 2021). Increasingly, this assumed feasibility of net global removal of carbon extends to climate overshoot pathways, where the temperature limits of the Paris Agreement are temporarily exceeded. High level communication of climate science often frames the possibility of a temperature overshoot as a given; for example headline statement B.7 of the IPCC AR6 synthesis report presents the option of temperature overshoot in certain terms: "If warming exceeds a specified level such as 1.5°C, it could gradually be reduced again by achieving and sustaining net negative global CO_2 emissions." .

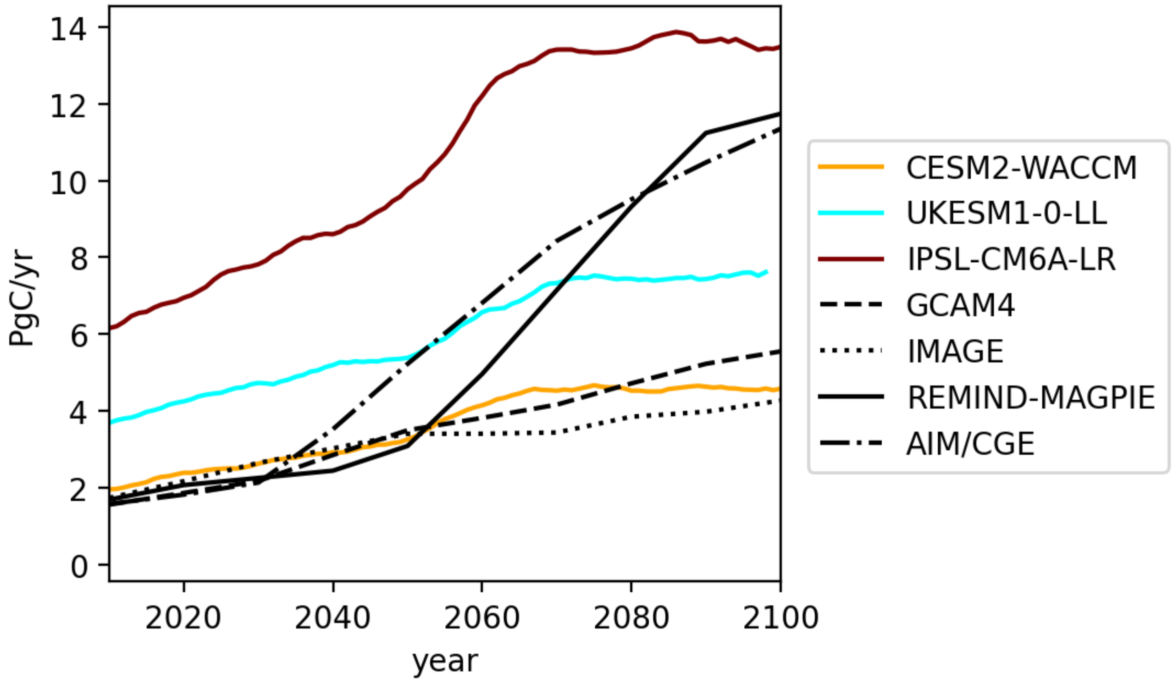
The plausibility of large scale CDR is subject to both geophysical and technological uncertainties, which vary by method, but are not captured in the current IAM and ESM modeling framework. For example, large scale bioenergy production for BECCS would have potential biophysical and biogeochemical feedbacks on the climate system that are not currently represented by the IAM-simple climate models used to define scenarios (Koch et al., 2021; Luyssaert et al., 2018; Melnikova et al., 2023). For land-based CDR approaches, the carbon sinks assumed within IAMs for a given land use transition are themselves subject to climate-induced risks due to warming (drought, wildfire, insect outbreaks (Anderegg et al., 2022; McDowell and Allen, 2015; McDowell et al., 2020) which are not taken into account in IAM scenarios which rely on approaches such as Bioenergy Carbon Capture and Sequestration (BECCS) for large scale carbon removal (Kato and Yamagata 2014; Muri 2018). In addition, carbon sink strengths themselves respond dynamically to emissions and removals of gases through carbon concentrations, aerosol forcing, and surface ozone (Sonntag et al., 2018; Mengis et al., 2019; O'Sullivan et al., 2021; Zhang et al., 2021) - dynamics which can only be represented in an emission-driven, process resolving model structure. Ocean based CDR suggestions such as alkalinity enhancement (Fakhraee et al., 2023; Hartmann et al., 2023) or iron fertilization (Emerson, 2019) are also conditional on the wider climate state and can have significant non-local effects on the wider biosphere (Keller et al., 2014).

We can illustrate in Figure 3 the scale of these potential uncertainties in the feasibility of land-based CDR capacity using a pair of scenarios from CMIP6; the highest emission member of the ScenarioMIP ensemble (SSP5-8.5) and the extreme overshoot scenario SSP5-3.4-overshoot (Kriegler et al., 2017; Riahi et al., 2017), which assumes a significant amount of BECCS is deployed in the latter half of the 21st century (with bioenergy crop production of 9PgC/yr by 2100). In CMIP6 ScenarioMIP, both SSP5-8.5 and SSP5-3.4-over input datasets for CMIP were conducted by the REMIND-MAGPIE IAM, but experiments were also mirrored in other IAMs. Figure 3a illustrates that the IAMs are more in agreement on the carbon content of current total harvest, but they differ in future projections under the SSP5-3.4-over scenario. Only a small subset of models conducted this simulation in CMIP6, but they are in significant disagreement about the current harvest level – highlighting a potential bias which would require further calibration if BECCS fluxes were calculated internally in ESMs.

We can get some intuition for the ESM simulated additional bioenergy production required for the BECCS-based carbon removal in SSP5-3.4-over by assessing the difference between total harvest in SSP5-8.5 and SSP5-3.4-over (Figure 3b).

The difference in harvest in REMIND-MAGPIE notably exceeds the difference between ESM simulated harvest flux in SSP5-85 (where there is no deployed BECCS) and SSP5-3.4-over in all 3 of the models considered (difference between purple and red lines, Fig. 3), indicating that none of these models would be able to replicate the level of negative emissions assumed in REMIND-MAGPIE – despite being driven by land use transitions derived from that model. Notably, other IAMs also vary significantly in their assumed harvest fluxes (indicating a varying reliance on BECCS for carbon capture). Again, this highlights that if future climate simulations allowed BECCS fluxes to be calculated internally within the ESMs, there could be significant additional variance in the simulated forcing trajectory of large overshoot scenarios.

(a) Total Crop Harvest



(b) Difference in Harvest (SSP534over - SSP585)

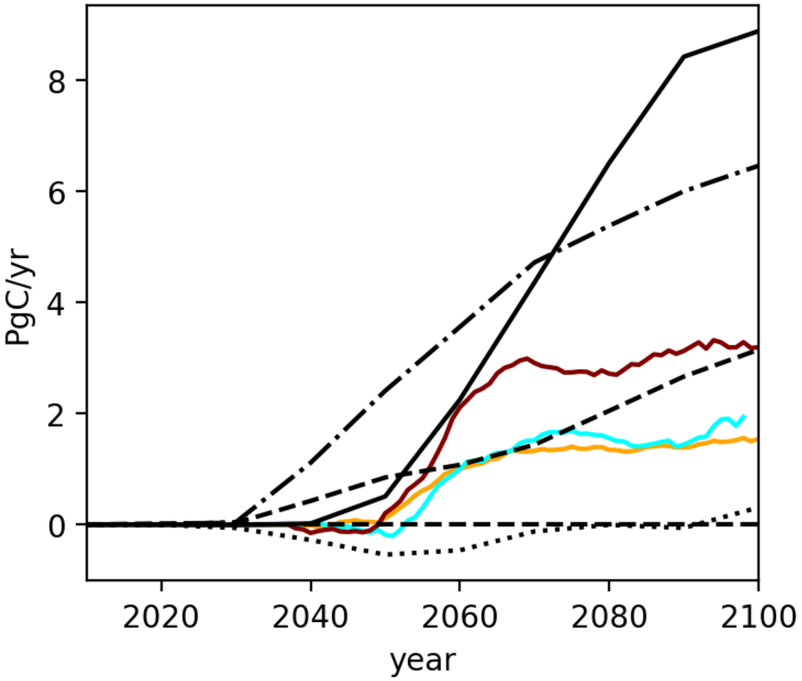


Figure 3: (a) An illustration of total harvest carbon flux as simulated in the SSP5-3.4-overshoot scenario as simulated by the the SSP5 marker model (REMIND-MAGPIE, solid black) and other integrated assessment models (dotted and dashed black lines), compared with estimates from 3 Earth System models (colored lines) which completed both simulations. (b) colored lines show the simulated difference in ESMs (IAMs in black) between harvest carbon flux in SSP5-3.4-overshoot and SSP5-85.

Issues over the feasibility of CDR at scale are compounded by uncertainties in the response of the Earth System to extended periods of net zero or net negative emissions. Much of current understanding stems from highly idealized ESM experiments which have been conducted by only a subset of models (Jones et al., 2019; Keller et al., 2018). Such experiments show that Earth System response to net negative emissions is complex and likely asymmetric, but the lack of extensive process-based ESM simulations of response to net negative emissions leaves significant uncertainties in cases in which SCMs and emulators have not been extensively tested or validated. Such uncertainties have bearing on the feasibility of a temperature overshoot, both in terms of the level of mitigation needed to stabilize warming (Jenkins et al., 2022) and the relative timing of net-zero and peak warming (Koven et al., 2023).

As such, concentration-driven mitigation scenarios created through the existing modeling chain may assume land-use and management carbon fluxes from the IAM which are impossible to achieve with the ESM (and perhaps reality) due to ecophysiological limitations of vegetation in a changing climate. An activity-driven framework for removals would directly assess these risks associated with land-based carbon mitigation (such as through afforestation, reforestation, forest management, biochar, agricultural soils or BECCS), by providing a range of potential outcomes for the land and ocean-based removal strategies which are employed in the scenario which can contextualize and provide uncertainty bounds for the climate trajectory simulated internally within the IAM.

An activity-driven framing is naturally suited to process representation of carbon dioxide removal methods (especially for those methods which rely on the manipulation of natural systems which are to some degree resolved within Earth System Models). Some of these (such as afforestation) are already represented within most ESMs, while others (BECCS, soil carbon enhancement, terrestrial and marine alkalinity enhancement, blue carbon enhancement) are represented to a lesser degree or not at all. A dedicated activity within CDRMIP could assess the effectiveness of different approaches in a semi-idealized context under different climate background states. Such an activity could aid in the interpretation of emissions-driven scenario simulations in CMIP7 and provide a pathway to the inclusion of a wider range of CDR technologies in CMIP8 and beyond.

Resolving compound tipping points and adaptation challenges as a function of emissions

The potential for nonlinearities and tipping points in the climate system is frequently raised as a motivator for urgent emissions cuts (Lenton et al., 2019), and often framed in terms of temperature thresholds (for example, in discussion of whether rapid and irreversible changes might be triggered if 1.5°C of warming above pre-industrial levels is exceeded (Armstrong McKay et al., 2022)) - but introducing previously ignored nonlinearities can complicate how thresholds defined in terms of temperature map onto mitigation risks. Some of these previously discussed system thresholds have the potential to alter global scale carbon-climate feedbacks and dynamics e.g. the risk of crossing cryosphere thresholds (Kloenne et al., 2022), forests may be subject to dieback or changes in carbon sink efficacy (Chai et al., 2021) and increased stratification of the ocean may change its heat and carbon uptake dynamics (Bourgeois et al., 2022).

As such, tipping points and emissions are intricately tied together and Earth System Models are natural tools for simulating how they might interact, with increasingly complete and sophisticated process resolution for ecosystem and cryosphere and ocean processes. Understanding how these nonlinearities combine, and relate to a wider mitigation strategy requires the processes to be simulated in a self-consistent framework in the context of a emissions-driven mitigation scenario where carbon-climate feedbacks are interactively resolved.

This argument extends to adaptation planning, where ESM results from concentration-driven simulations are often currently framed in terms of expected impacts at given warming levels (Jevrejeva et al., 2018; Lwasa et al., 2018; Intergovernmental Panel on Climate Change (IPCC), 2022; Travis et al., 2018) rather than impacts under given emissions pathways (Drouet et al., 2021; Wiebe et al., 2015). As such, adaptation planners have no simple means of assessing the range of plausible hazards consistent with a given level of climate policy. Emissions-driven simulations could help fill this gap, while still allowing impacts to be framed in terms of warming levels as they are with existing ensembles.

Better assessment of ocean acidification

The IPCC AR6 WG I report highlighted the limitations of concentration-driven experiments in CMIP6 for projecting future ocean acidification (Intergovernmental Panel on Climate Change, 2023). Inter-model variance in surface pH is very low in a given scenario (Lovenduski et al., 2016), largely because all ocean models experience identical surface CO2 concentrations (Kwiatkowski et al., 2020). Emissions-driven simulations would represent the full joint dynamics of ocean and atmosphere heat and carbon evolution(Terhaar et al., 2023). Such factors would represent an improvement in the categorisation of uncertainty in any Earth System processes which are directly or indirectly dependant on atmospheric CO_2 concentrations.

Diagnosis of land use emissions

There remains significant uncertainty in both the simulation and the assessment of observed emissions due to land use change (Friedlingstein et al., 2022b). In concentration-driven simulations in CMIP6, land use emissions calculated internally in each model, and were consequential in terms of derived compatible fossil emissions (Liddicoat et al., 2021), and land use emissions are assessed independently in LUMIP (Lawrence et al., 2016). However, there remains significant uncertainty on the definition and quantification of land use fluxes. In the Global Carbon Budget(Friedlingstein et al., 2022b), for example, best estimates of land use emissions are derived from bookkeeping models (Hansis et al., 2015; Houghton and Nassikas, 2017; Quilcaille et al., 2022) which use empirical growth curves to estimate the transient carbon stock response to land use changes. Meanwhile, national inventories use different accounting conventions to those used in IAMS, ESMs and bookkeeping models – including not just transitions in land use, but also including land sinks in some regions whose usage remains static, but which are designated as managed (Gidden et al., 2023; Grassi et al., 2021).

Verification of emissions reductions

The 2028 Global Stocktake will be the next major global assessment of progress towards Paris Agreement goals. This requires increasing understanding of how to quantify and verify national emissions reductions. Existing approaches for the detection and attribution of observed climate changes to different historical anthropogenic activities rely predominantly on models in concentration driven mode (Hegerl and Zwiers, 2011). However, with increasing focus on mitigation activity and the verification of reductions in terms of climatic variables (such as greenhouse gas concentrations, temperatures or heat uptake)(Peters et al., 2017), it makes sense to consider the detection problem in terms of emissions - when can the benefits of mitigation activity be observed?

As climate mitigation ambition ramps up, there is a growing expectation that emissions will change their recent historical trend, initially with slower growth, then a peak, followed by a decline. Already, global CO_2 emissions have slowed from 3% per year growth in the 2000s to 1% per year growth in the 2010s (Friedlingstein et al., 2022a). An increasingly relevant question will then be to what degree any reductions will be detectable in terms of observed climate variables and near-term warming (McKenna et al., 2020; Samset et al., 2022) and, potentially, climate impacts themselves (Mendez and Farazmand, 2021; Ciavarella et al., 2017). These questions are of relevance for the justification of climate policy, both globally and at the country level, and for planning for potential near-term impacts and for assessments of liability for climate damages.

Modeling to support such activity requires a joint assessment of land, ocean and atmospheric carbon pool and human activity in a self-consistent framework (Ilyina et al., 2021). Land sinks are of particular relevance in the context of the Global Stocktake process which assesses national-level progress in the context of meeting obligations under the Paris Agreement. In this process, many countries offset a fraction of their emissions using managed land within their borders which is currently assessed to act as a carbon sink (Grassi et al., 2021). Understanding the robustness of these sinks in present and future divergent climates is thus critical in assessing the degree to which countries can rely on such sinks to substitute for emissions reductions on different timescales (Giebink et al., 2022).

In the atmosphere, efforts to detect emissions reduction from globally averaged atmospheric concentrations have not yet succeeded. It was expected that a two percentage point change in the growth rate of CO_2 emissions could be detected in the atmosphere with reasonable confidence after about 10 years (Peters et al., 2017). A possible explanation for the lack of signal is our inability to fully model and explain the inter-annual variability in climate-carbon feedbacks, which could be offsetting a part of the expected change in trend (Spring et al., 2020). In the years ahead, when emissions are hopefully declining, there will be a need to understand how the carbon cycle may respond with carbon-climate feedbacks potentially offsetting some of the expected declines in the atmospheric growth rate. Such experiments have to date been idealized (Keller et al., 2018; Jones et al., 2019), but there remains a need for integrated simulation to explore the interaction of natural carbon feedbacks with process-resolving CDR and non-CO2 emission pathways.

To date, attempts to verify emissions reductions as a function of atmospheric concentrations have been conducted in simple climate models (Abdulla et al., 2023), by adjustments computed from compatible emissions in Earth System Models (Spring et al., 2020) or by using atmospheric inversion models to compute emissions consistent with prescribed concentrations (Deng et al., 2022). These estimates would be well supported by fully self-consistent internally generated representations of the chain of causality from emissions to concentrations which could be achieved in emissions-driven ESM simulations.

Such questions could be addressed in DAMIP (Gillett et al., 2016)) or other activities using a combination of idealized and realistic simulations: (1) idealized experiments where CO_2 emissions reduce at a fixed rate to detect timing of signal emergence, (2) emissions-driven single forcer experiments to assess the detectability and linearity of the historical climate response to different anthropogenic emissions. As such, hybrid emissions-driven simulations would provide a critical complement to existing verification efforts, potentially including counterfactual scenarios which could illustrate when mitigation policy implementation becomes detectable in terms of atmospheric concentrations or climate impacts (Tebaldi and Friedlingstein, 2013).

3 Recommendations for emissions-driven experiments in CMIP7

Past CMIP phases designed experiments to exploit the existing modeling capacity in major Earth System modeling centers at the time of experimental design, motivated by dominant uncertainties and pilot studies in the literature (Meehl et al., 2007; Taylor et al., 2012; Eyring et al., 2016). Early climate simulations used atmospheric-only models to diagnose radiative feedbacks (Cess et al., 1989). CMIP2 era coupled experiments generally exploited radiative flux corrections to maintain a stable ocean temperature (Covey et al., 2003), and a parallel Atmospheric Model Intercomparison Project (AMIP) process remained to understand atmospheric feedbacks without the added complexities of ocean coupling (Lawrence Gates et al., 1999). The presence of an intercomparison project fostered rapid improvements in coupled simulation such that by the time of the CMIP3 ensemble (Meehl et al., 2007), there was increasing acceptance that resolving coupled ocean-atmosphere processes was key to understanding climate projections (Frame et al., 2006), and models were rapidly advanced so that they could maintain stable climates without flux corrections.

Over the last 20 years, the scope of process resolution in climate models has further expanded (Figure 3), and the increasing complexity of both atmospheric chemistry and aerosol treatment has increased the degree to which some emissions are already represented in many climate models and interact with climate feedbacks (Thornhill et al., 2021). The evolution of aerosol treatment from CMIP3 to CMIP5 to CMIP6 has seen a non-uniform tendency for models to represent aerosol indirect effects on clouds, and emissions-driven aerosol processes (interactive treatment of aerosols have been included in some fraction of Earth System Models since CMIP5 (Eyring et al., 2016), and stratospheric aerosols have been included since CMIP3 (Meehl et al., 2007)). CMIP6, in particular (Eyring et al., 2016) introduced an tiered experimental design which accommodated models with varying levels of aerosol and atmospheric chemistry implementation in scenario experiments, supported by dedicated sub-MIPs to assess processes (in AerChemMIP) and effects of different forcers (in RFMIP).

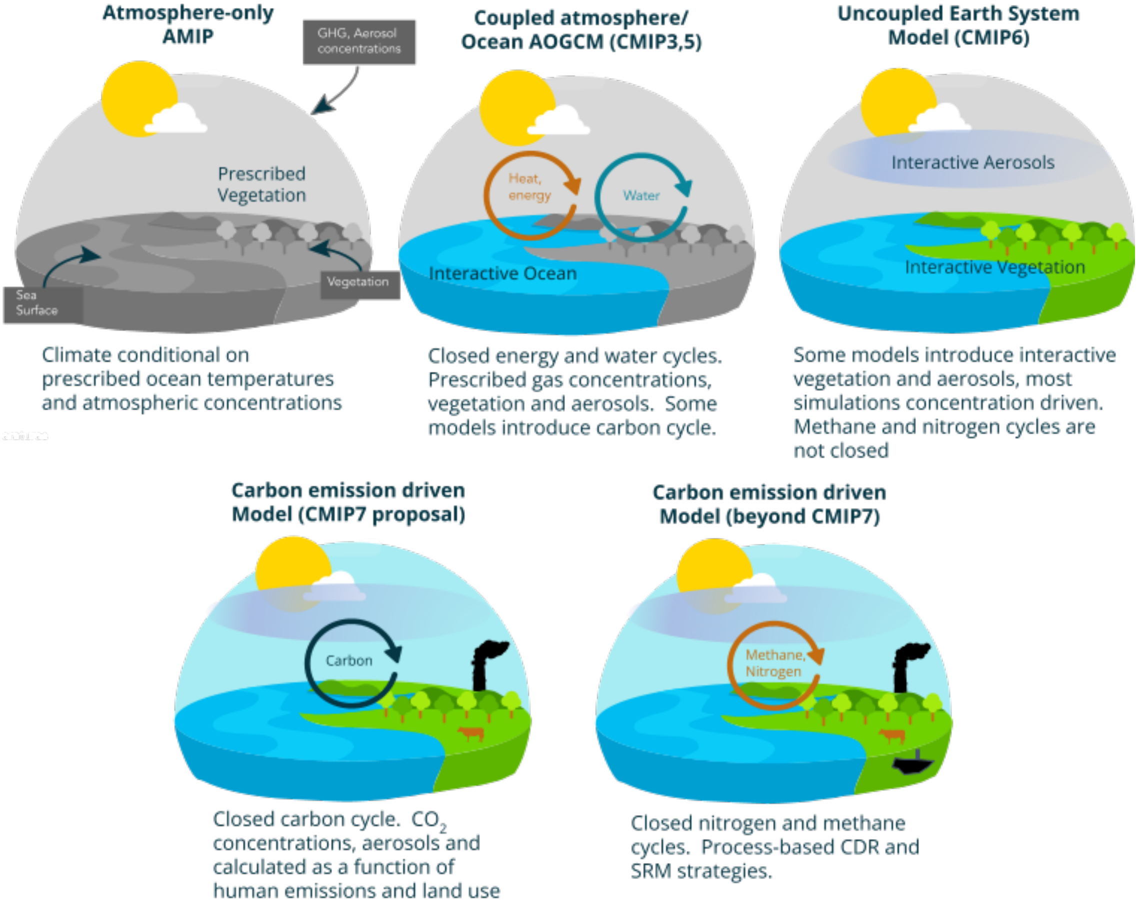


Figure 4: the evolving dominant paradigm in different generations of CMIP, including this study's recommendations for CMIP7 and CMIP8

Past phases of CMIP have defaulted to concentration-driven scenarios, but models capable of running with a closed and interactive carbon cycle have been developed by some centers for over two decades (Cox et al., 2000; Joos et al., 1999; Fung et al., 2005), with intercomparison efforts for coupled carbon Earth System Models coming soon after (Friedlingstein et al., 2006; Jones, 2020). These early studies established the significance of coupled carbon-climate processes in the wider evolution of the Earth System, with potential interactions between carbon balance and ocean circulation (Joos et al., 1999), feedbacks with the terrestrial biosphere (Cox et al., 2000) and weakening carbon sinks at higher warming levels (Fung et al., 2005).

However, despite increasing acknowledgment of the central role of coupled climate-carbon dynamics in determining the outcome of mitigation policies (Allen et al., 2009; Holden et al., 2018), only 19 out of 82 CMIP6 model configurations participated in the Coupled Climate–Carbon Cycle Model Intercomparison Project (C4MIP) in CMIP6 (Jones et al., 2016), though these models vary in resolved processes (12 resolving carbon-climate interactive feedbacks, 5 resolving phytoplankton biophysical interactions, 3 resolving biogenic aerosol-cloud feedbacks and no models representing non-CO_2 biogeochemical cycle feedbacks (Séférian et al., 2020)).

Nonetheless, hybrid emissions-driven experiments in the 'central' DECK/Historical part of CMIP6 were limited to *esm-historical* and *esm-picontrol* (Eyring et al., 2016). Further, the DECK required independent *picControl* and *esm-piControl* simulations from an ESM, and highlighted the importance of large ensemble sampling for the historical simulation. In practice, for models which conducted the ESM historical simulation *esm-hist*, it was generally without initial condition sampling - presenting an obstacle for the assessment of the role of internal variability in carbon cycle feedbacks, and for signal emergence of coupled Earth System processes (Li and Ilyina, 2018) and near-term initialized climate prediction systems (Li et al., 2023a) which enable near-term prediction of atmospheric CO_2 concentrations, air–sea and air–land carbon fluxes.

The limited ESM-DECK experiments in CMIP6 were supported by process understanding from idealized carbon cycle feedback experiments, including the globally aggregated effects of idealized carbon dioxide removal in CDRMIP (Keller et al., 2018), metrics of carbon cycle feedbacks in C4MIP (Jones et al., 2016and ZECMIP (Jones et al., 2019) and the physical and carbon effects of land use change in LUMIP (Lawrence et al., 2016)and LS3MIP (van den Hurk et al., 2016). Although C4MIP included some hybrid emissions-driven scenarios - (*esm-ssp585* and *esm-ssp534-over*), these represent very large near-term emissions which are distant from contemporary policy discussions (Hausfather and Peters, 2020a).

3.1 A coupled climate-carbon ESM representation for CMIP7

As such, we argue that in order to provide robust information for both adaptation and mitigation, it is equally important to sample inter-model uncertainties in the wider carbon-climate system. This requires a change in prioritization in the DECK, ScenarioMIP, and elsewhere in CMIP, with default control, historical, and projection simulations run in hybrid emissions-driven configuration, with concentration driven options used as a fallback for models which cannot process emissions. Such a reprioritization would enable modeling centers to more efficiently use resources to focus on Earth System uncertainties (including physical and carbon cycle elements), rather than splitting resources.

We argue that carbon-climate interactions and feedbacks are central to how the coupled Earth system will evolve in the future and therefore need to be central to CMIP activities going forwards rather than an optional extra. For CMIP7, this requires that carbon emissions and land activity driven simulations become the default for those models which are capable. ESMs in this configuration require the ability to process anthropogenic carbon emissions from fossil fuels and land use change and management in the context of a closed and stable carbon cycle, which represents oceanic and land-based sinks. For these models, CMIP7 historical and scenario experiments could be driven by fossil carbon emissions and land use transitions. For ESMs without the capacity or desire to run in hybrid emissions-driven configuration, scenarios based on simple climate models could still be computed in the conventional ScenarioMIP structure, with guidance that the concentration pathway represented within ScenarioMIP is only one potential outcome of climate policies in terms of emissions, atmospheric concentrations, and climate and carbon cycle responses. Alternatively, non-ESM AOGCMs could be driven by small ensembles of plausible concentration pathways, sampling a range of plausible carbon cycle uncertainty.

Participation in CMIP by models with heterogeneous complexity is not unprecedented. In CMIP5 (Taylor et al., 2012)and CMIP6 (Eyring et al., 2016), only some models were capable of processing aerosol emissions (including aerosol-cloud interactions and feedbacks on natural aerosol emissions such as biomass burning, dust and sea spray) while those without interactive aerosol schemes were driven by predefined loadings (Stevens et al., 2017). In CMIP3 (Meehl et al., 2007), there was a similar coexistence between models with a thermodynamic slab ocean and those with a fully dynamic ocean (though slab oceans were abandoned in CMIP5). These periods of coexistence of model complexity proved a necessary and very successful compromise to allow this diversity on the path towards a successful transition to increased complexity across the CMIP ensemble. We argue that now is the right time for the next planned transition to emissions-driven modelling capability.

3.2 Coordinated effort on activity-driven carbon cycle modeling

The status quo which defined the default configurations in CMIP6 and earlier phases is now changing. Models can increasingly resolve vegetation and soil carbon dynamics including permafrost, as well as marine biogeochemical cycles. For many ESMs, the capability to represent these processes now exists, but relatively little work has been done thus far to comprehensively understand how this complexity impacts the trajectory of climate, especially under deep mitigation scenarios, geoengineering proposals, and overshoots.

ESMs can potentially add self-consistent process resolution to a wide range of carbon processes which are currently resolved in scenarios in an *ad hoc* and quasi-empirical fashion. ESMs are already well placed to resolve natural land and ocean carbon sinks, and are operationally used to quantify these terms today (Friedlingstein et al., 2022a). But in addition to this, they can directly inform the effectiveness and uncertainty associated with land use and management policy, and their coupled interaction with natural sinks (Lawrence et al., 2016). Beyond this, many high ambition scenarios contain significant requirements for explicit representation of carbon dioxide removal (Fuss et al., 2014; Anderson and Peters, 2016) whose plausibility can potentially be assessed when represented in an Earth System Model (Muri, 2018). Increasing understanding of how to map between national accounting systems and ESM/IAM output (Gidden et al., 2023; Grassi et al., 2021) can be strengthened with hybrid emissions-driven simulations (combined with well chosen counterfactual experiments in LUMIP), where ensembles can provide ranges of modelled direct and indirect anthropogenic fluxes from land use change.

A hybrid emissions-driven scenario framework would allow for the explicit representation of different forms of human activity associated with carbon mitigation, and much of this has already been demonstrated using subsets of ESMs. Carbon removal technologies (such as bioenergy carbon capture and storage) could largely use existing models combined with sub-annual harvest cycles, harvest-age for woody biomass, and a dedicated pool to represent underground carbon storage. Others, such as cultivation and harvesting of oceanic algae (Wu et al., 2023) or ocean alkalinity enhancement (Keller et al., 2014; Ilyina et al., 2013; Burt et al., 2021; González et al., 2018), could be represented with explicit parameterisations (Wu et al., 2023). And, as discussion of the ethics and risks of solar radiation management intensify (Reynolds, 2021; Sovacool, 2021), understanding the interaction between geoengineering and ecosystem processes is of paramount importance (Zarnetske et al., 2021) where coupled ESMs are essential in any comprehensive cost-benefit assessment (Sonntag et al., 2018).

Thus, although there is a large and growing body of work assessing mitigation strategy in the context of emission-driven models, much of this to date has been in the context of isolated ESM experiments which do not capture multi-model uncertainty (with the exception of the idealized adaptive mitigation pathways explored in (Silvy et al., 2024)). By adopting a hybrid emissions-driven design, CMIP7 could directly inform the coupled system risks associated with the range of carbon removal and geoengineering strategies which increasingly play an outsized role in the mitigation debate.

3.3 Diagnostic simulations in the CMIP7 fast track

Here we discuss the likely implementation of emissions-driven simulations in CMIP7 at the time of writing. As in CMIP6, CMIP7 will contain a "DECK" which (as in CMIP6) will request *esm-picontrol* as a starting point for emissions-driven simulations. Current plans for CMIP7 will also consider *historical* and *esm-historical* as part of the DECK (CMIP phase 7 (CMIP7), 2024). In addition, the CMIP7 'fast-track' is a set of high priority experiments which will be recommended for completion in time to inform assessment reports for the IPCC AR7 cycle (CMIP phase 7 (CMIP7), 2024), see Table 1. With a higher focus on emissions-driven experiments, we are recommending (and it is currently planned) that the fast track will include both emissions-driven scenarios and diagnostic simulations which will help assess key aspects of emissions-driven response. These idealized carbon emissions-driven experiments (which will be fully documented in a separate paper) will allow calculation of key carbon-climate metrics needed to inform climate policy tools such as the IPCC remaining carbon budget for climate stabilization, thus complementing existing concentration-driven metrics. Figure 5 illustrates a proposal for a set of diagnostic emissions-driven experiments which would provide emissions-driven estimates of TCRE and ZEC in fast track.

experiment	**Forcing (CO_2)**	**Forcing (other)**	**branches from**	**Relevance**
CMIP7 DECK				
esm-piControl	1850 constant	1850 constant	esm-piControl-spinup	Stable control climate for e-driven climate
esm-piControl-spinup	1850 constant	1850 constant	-	Pre-equilibrated spinup stage for ESM configurations
esm-historical	historical fossil & industrial CO_2 emissions plus land-based activities	Historical concentrations for non-CO_2 forcers	esm-piControl	Provides historical climate assessment and initial states for e-driven scenarios
esm-flat10	fixed CO_2 emission rate (10GtC/yr) for at least 150 years to ensure 2x	1850 constant	esm-piControl	Emissions-driven estimate of TCRE, reaches exactly 1000PgC in 100 years

	CO_2 concentrations are reached			
CMIP7 fast track				
esm-flat10-zec	zero emissions branching from flat10 in year 100	1850 constant	flat10	Idealized calculation of ZEC from flat10 expt, branch in year 100
esm-flat10-cdr	Linearly declining emissions by (2GtC/yr)/decade from 10GtC/yr (year 100) to -10GtC/yr (year 200). Constant -10GtC/yr (years 200-300)	1850 constant	flat10	Idealized calculation of climate reversibility under negative emissions, branching from flat10 experiment.
esm scenarios	future fossil & industrial CO_2 emissions plus land-based activities	future concentrations for non-CO_2 forcers	esm-historical	Policy-relevant future scenario simulations

Table 1: Current plans for the implementation of emissions-driven simulations in the CMIP7 DECK and fast track

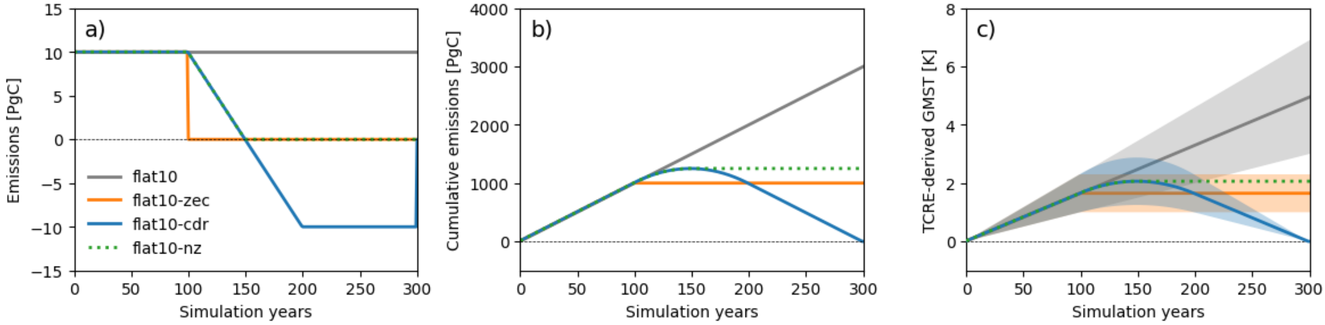


Figure 5: Illustrations of recommended idealized diagnostic experiments (Table 1) for the CMIP7 fast track, showing (a) emissions (b) cumulative emissions and (c) temperature as a function of time. Shaded spread in (c) is defined assuming perfect cumulative emissions and the IPCC AR6 assessed range of TCRE (Masson-Delmotte et al., 2023)**. Solid lines are recommendations for CMIP7 fast track, dashed lines are additional recommendations for C4MIP in CMIP7.**

esm-flat10 – diagnostic simulation for transient response

Esm-flat10 would consider a constant annual flux of 10PgC of carbon for 100 years (such that the warming after 100 years would correspond to 1000PgC of cumulative emissions - as such, a direct measure of TCRE). Unlike for *1pctCO2,* compatible emissions do not need to be computed and the TCRE can be easily calculated as a time average in the experiment, thus providing a clean experiment which can be branched to assess zero emissions commitment and climate reversibility. *Esm-flat10* as a default diagnostic for TCRE would have a number of desirable properties: (1) emissions are constant for all models considered (rather than varying by model under *1pctCO2 - see Figure A1*), (2) emissions are constant at approximately current rates throughout the simulation (rather than weighted towards the end of the simulation in *1pctCO2*), (3) peak emission rates are more consistent with those of ambitious climate mitigation scenarios than the diagnosed peak emission rates in *1pctCO2* at the point of reaching 1000PgC cumulative emissions are.

esm-flat10-zec – diagnostic simulation for zero emissions commitment

We propose a completely emissions-driven alternative derivation for Zero Emission Commitment: *esm-flat10-zec.* The zero emissions commitment is a measure of the path-dependence of the temperature to cumulative emissions relationship (Koven et al., 2023), an estimate of the subsequent global warming that would result after a period of anthropogenic emissions, once they are set to zero (Jones et al., 2019; MacDougall et al., 2020). ZECMIP (Jones et al., 2019) contains a number of experiments to quantify this behavior, most predominantly with the *esm-1pct-brch-1000PgC* experiment, which branched from the concentration driven *1pctCO2* at the point at which 1000PgC of cumulative emissions had been emitted. *Esm-flat10-zec* allows for computation of temperature changes after an immediate cessation of emissions, similar to the ZEC concept assessed in (Jones et al., 2019).

E*sm-flat10-zec* would convey a number of both practical and theoretical advantages over *1pctCO2* as a primary diagnostic of Zero Emissions Commitment. (1) The maximum rate of CO2 emissions in *esm-flat10* (10 Pg C/yr, vs ~20 Pg C/yr for *1pctCO2*) is closer to realistic values that are projected for ambitious policy scenarios, where emissions must peak and decline from their present values of ~10 Pg C/yr within decades to achieve Paris Agreement-compatible warming targets. (2) Because the experiment is emissions-driven from the outset, it would not require a change in configuration at the branch point, (3) The branch point is identical for all models (unlike in *esm-1pct-brch-1000PgC,* where the year in which 1000PgC of compatible cumulative emissions is exceeded must be calculated retrospectively to find the appropriate branch year). (4) This common experimental setup would allow the easier automation of ensembles in the calculation of both TCRE and ZEC, without needing to calculate compatible emissions to find the appropriate branch point.

esm-flat10-cdr – diagnostic simulation for climate reversibility

An increasing feature of the discussion of future Paris-Compatible pathways is an assessment of the reversibility of the climate system, both in a global sense (Zickfeld et al., 2013; Wu et al., 2015) and in terms of regional and subsystem responses (Armour et al., 2011; Martin et al., 2022). In CMIP6, a number of idealized experiments were conducted under CDRMIP (Keller et al., 2018) which included a concentration-driven extension of *1pctCO2* called *1pctCO2-cdr* (see Figure 8), which prescribed a 1% rampdown in concentrations at the point at which *1pctCO2* reached quadruple pre-industrial levels. This experiment undergoes a large discontinuity in compatible emissions at the transition from upwards to downwards branches, making it less useful as an indicator of realistic transitions to negative emissions (see Figure 8) (Koven et al., 2023).

Here we propose an emissions-driven extension to *esm-flat10* to address this need: *esm-flat10-cdr* would serve as an emissions-driven idealized experiment to assess the dynamics of climate reversibility under reducing emissions and net-negative emissions. The experiment would allow for a number of simple idealized diagnostics which would be relevant to the net zero transition and the response of the system to net negative emissions. *esm-flat10-cdr* would branch from *esm-flat10* in year 100, after 1000PgC of emissions, ramping down emissions linearly over 100 years from +10PgC/yr to -10PgC/yr and then maintaining a negative flux of -10PgC/yr for an additional 100 years.

This *esm-flat10-cdr* experiment would provide a number of advantages over *1pctCO2-cdr*: (1) an emissions-driven metric of climate reversibility with a continuous emissions timeseries, (2) an idealized net-zero transition to measure the lags in the climate system in the decades around net-zero as emissions pass from net positive to net negative, (3) characterization of asymmetries in the climate response relative to emissions rather than to concentrations, by using a symmetric and continuous reversal from positive to negative CO_2 emissions, and (4) initial emissions and a decarbonisation rate which are comparable to an aggressive mitigation scenario. These features are all also present in the gaussian cumulative emissions experiment described by (Koven et al., 2023), which also features an asymptotic rise in emissions at the start of the industrial period and an asymptotic tapering of negative emissions to zero as cumulative net zero emissions is achieved. The key advantage of *esm-flat10-cdr* over *esm-restoration* for an ESM-DECK is that it allows computational savings by re-using the first common 100 years of *esm-flat10* and *esm-flat10-zec* to form a coherent set of interrelated experiments and metrics.

A final experiment – not recommended for fast track, but for possible inclusion in a CMIP7 satellite MIP such as C4MIP would be *esm-flat10-nz,* branching in year 150 from esm-flat10-cdr, allowing an assessment of zero-emissions response under an idealized gradual decline from current emissions rates to net zero. This experiment would provide a companion experiment to *esm-flat10-zec,* assessing how zero emissions response differs between an instantaneous cessation and a gradual approach to net zero (Koven et al., 2023).

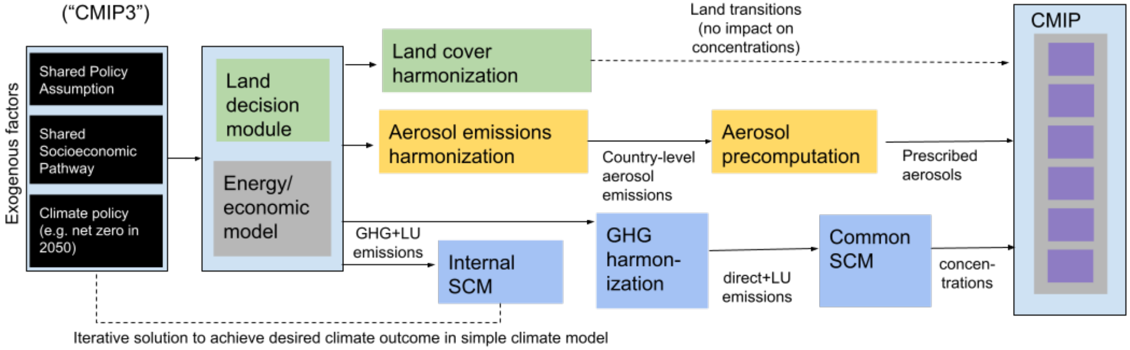
3.4 IAMs and scenario development

Emissions-driven simulations to date in CMIP have been highly idealized (e.g. ZECMIP(Jones et al., 2019)). An emissions-driven focus allows coupled system processes to be represented in policy relevant scenarios, but this requires a refinement in the way that scenarios have traditionally been framed and categorized (O'Neill et al., 2016). In hybrid emissions-driven mode, ESM simulated concentrations, radiative forcing, and temperature will differ from that in the scenario definition (currently harmonised SCM simulations combining historical climatic trends and IAM driver data) (Figure 6c). Furthermore – the ability to simulate different types of carbon removal processes and non-CO_2 mitigation strategy within the ESM opens the door to having multiple scenarios with comparable best estimate temperature outcomes in the IAM, but with different uncertainty ranges simulated in the ESM ensemble. As such, the naming strategy for emissions-driven scenarios will ultimately need to represent a higher dimensional space, providing a shorthand for embedded characteristics on decarbonization rate, removal strategy and non-CO_2 emissions. This may be more easily achieved with qualitative identifiers than with continuous labels referring to radiative forcing or temperature targets.

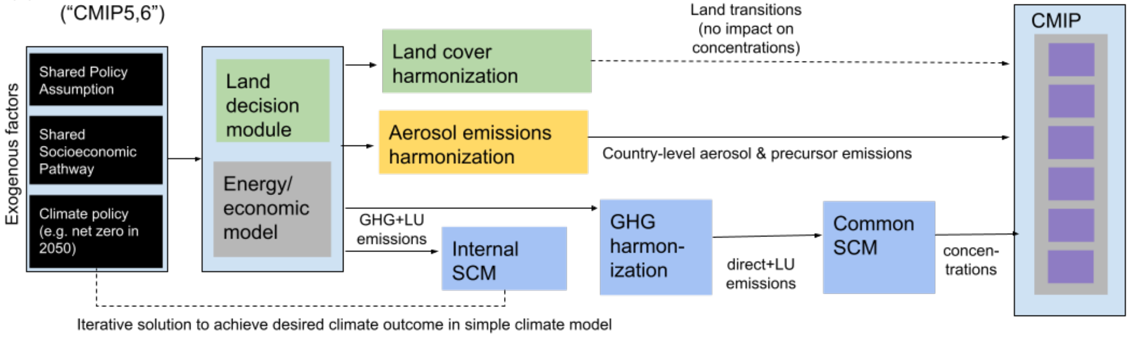
In practice, the policy strategies implemented internally in IAMs would still be informed by a climate outcome (e.g., Paris compliant scenarios), perhaps assessed using a simple climate model - but process uncertainties represented within the downstream ESM ensemble simulation may illustrate that some policies targeted at a given warming level are more robust than others (e.g. scenarios which rely heavily on afforestation which may or may not achieve desired carbon outcomes in all ESMs) or may have different negative impacts on other aspects of the global environment (e.g. air quality or food production capacity).

It is notable that some IAMs already contain process-based land surface models to inform land use emissions estimates (Stevanović et al., 2016). A key distinction in the hybrid emissions-driven framework would be that land use transitions (in addition to fossil CO_2 emissions), are provided by the IAM system - allowing a *diversity* of land use emissions to be simulated in the ESM ensemble (rather than the status quo where a single set of land use emissions are computed by the IAM) thus modeling the uncertainty in climate implications of land-use transitions.

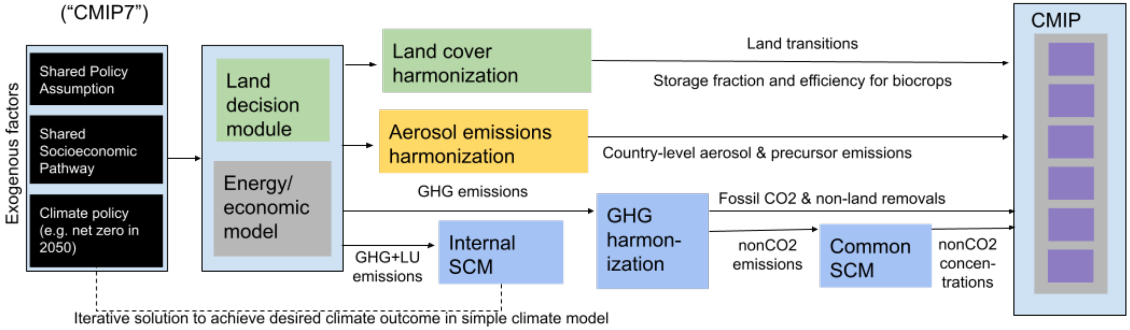
(a) GHG concentration driven model, predefined aerosols ("CMIP3")



(b) GHG concentration driven model, interactive aerosols ("CMIP5,6")



(c) Partial GHG e-driven model, interactive aerosols ("CMIP7")



(d) Complete e-driven model, interactive aerosols, SRM & CDR ("CMIP8+")

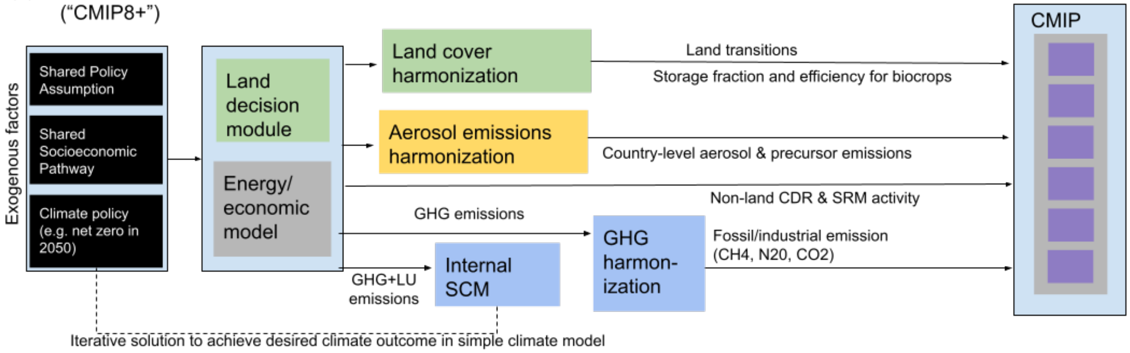


Figure 6: Stylized illustrations of the historical (a,b) and proposed (c,d) information flow for CMIP. (a) shows concentration-driven modeling pipeline with prescribed aerosols common in CMIP3 (b) shows concentration-driven modeling pipeline with interactive aerosols common in CMIP5,6 (c) a proposed scenario pipeline for hybrid emissions driven simulations in CMIP7 with carbon emissions but maintaining concentration definitions for non-CO_2 greenhouse gases (d) a proposed CMIP8 pipeline, with emissions driven configuration for CO_2, N_2O and CH_4 and process based implementation of CDR and SRM approaches

4 Limitations and new challenges

4.1 Coupled system biases

A challenge with running models in hybrid emissions-driven mode is the additional degrees of freedom associated with calibrating the coupled climate-carbon cycle system to reproduce both the joint evolution in historical concentrations of climate forcers and the historical warming increases. CMIP6 *esm-historical* simulations show most models (10 out of 13 models in C4MIP) fall within a range of CO_2 concentration range of 40ppm – representing some 20 years of historical emissions. This is significantly greater than the observational uncertainty (about 0.1ppmFriedlingstein et al., 2022a; IPCC 2021 WG1 Chapter 4), and we suggest that the remaining outlier models may require greater attention to calibration of historical CO2 concentrations if emissions-driven simulations are the only runs provided. This concentration uncertainty in the present day, however, is likely significantly smaller than the future uncertainty in CO2 concentrations. This is evident from the significantly greater future spread in CO2 concentrations in those models which conducted *esm-ssp585* in CMIP6 (200ppm in 2100 compared with 20ppm in 2014 (Loughran et al., 2023; Masson-Delmotte et al., 2023)). This is also supported by the growing spread in cumulative compatible emissions in different Earth System Models, with a multi-model range of 50GtC of cumulative emissions in 2020, compared with 100GtC in 2100 under *ssp119* and a 280GtC range in 2100 in *ssp245 [Supplemental Figure A1].* As such, the present day concentration uncertainty is not trivial, but is small compared with the future spread in concentrations which arise from the carbon-climate feedback uncertainty.

The spread in present-day concentrations results in a modest increase in the model uncertainty in warming represented by the distribution of historical warming in CMIP6 simulations and their concentration-driven historical analogs for models which completed both experiments (Figure 7b,c) – and inter-quartile range of 0.45ºC for warming in 2005-2014 compared with an 1850-1900 baseline in *esm-historical*, compared with 0.25ºC in the concentration driven historical experiment. Notably, using a more recent baseline period (1970-1990), the 'hot model' issue of overestimated recent warming (Hausfather et al., 2022) is apparent by considering the concentration driven historical recent distribution in the context of observations (figure 7d), but the higher variance of recent warming in the emissions-driven simulations result in the observed warming lying within the inter-quartile range of simulated warming. Having only coupled simulations available would likely increase the difficulty of isolating the sources of bias in simulations (i.e. isolating biases in the ecosystem and physical systems). As such, fully coupled simulations would be well complemented by concentration-driven simulations if sufficient computational time is available to assess the role of coupled processes in model bias.

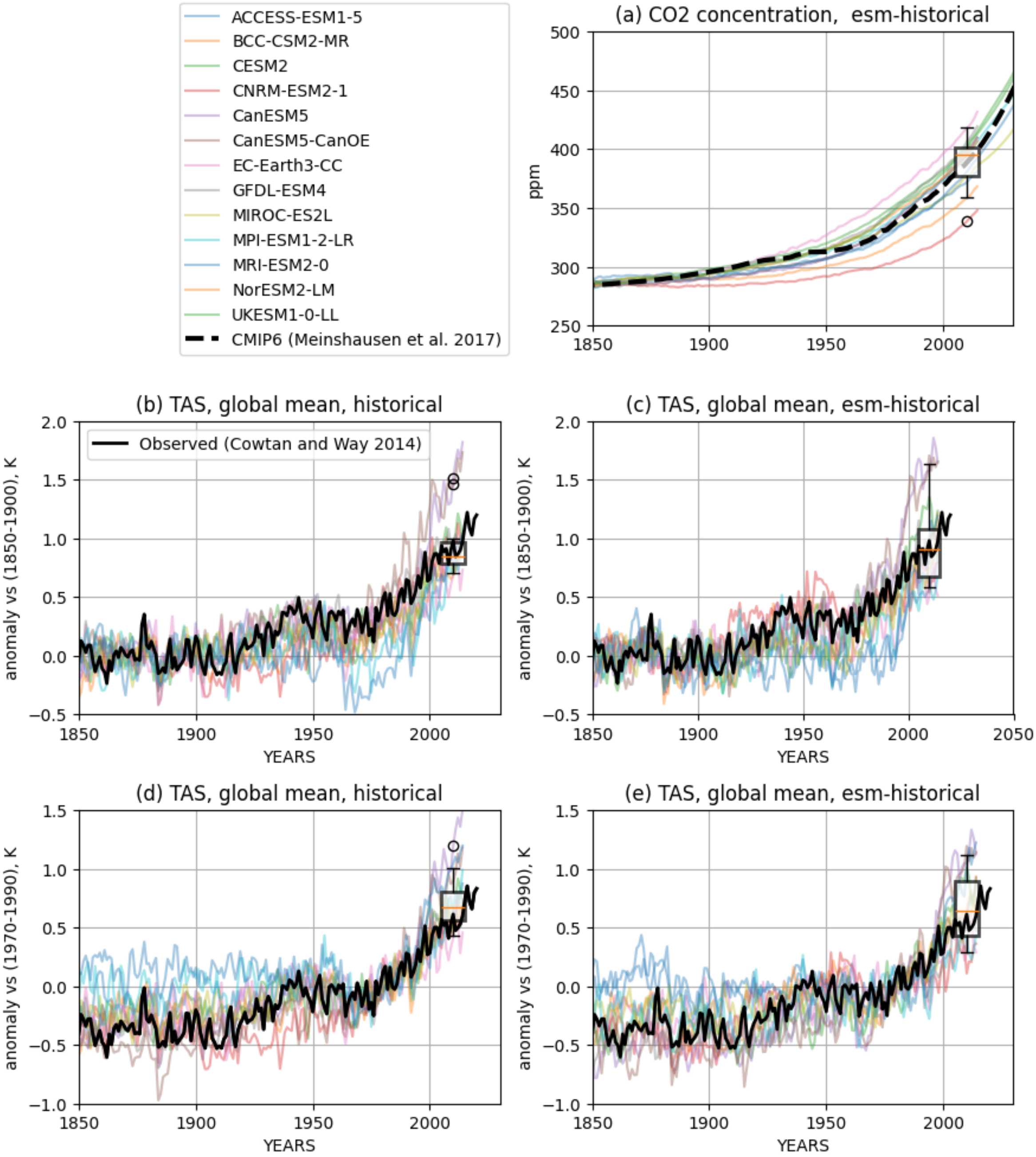


Figure 7: Carbon dioxide concentrations (a) and temperature anomalies (c,e) in emissions-driven historical simulations in CMIP6, and temperature anomalies concentration-driven historical simulations (b,d). Middle and bottom rows are relative to an 1850-1900

and 1970-1990 baseline respectively. Observed temperature data is from (Cowtan and Way, 2014) **Boxplots show the inter-quartile range (boxes) and 10-90 percentiles (whiskers) of the model simulated anomalies for the period 2005-2014.**

4.2 Implications for wider MIPs in hybrid emissions-driven simulations

The ‘hybrid’ approach proposed in this study considers a set of headline experiments in CMIP7 which are preferentially driven by carbon and aerosol emissions, with prescribed values for other atmospheric components. Such an approach would be supported by continued activities in RFMIP (Pincus et al., 2016) to provide diagnostics of global aerosol emissions-forcing-feedback dynamics, but also in AerChemMIP (Collins et al., 2017) which in CMIP6 assessed the role of aerosol forcing process uncertainty in future simulations.

There are some activities which did not exist under the CMIP6 platform which could be highly valuable in the increased understanding of emissions-driven processes. A dedicated activity to assess the role of regional aerosol emissions in this uncertainty (Wilcox et al., 2022) would address the growing consensus that shifts in regional emissions intensity has a large and detectable climatic impact (Samset et al., 2019; Liu et al., 2018). Aerosol processes can also be intricately linked with carbon uptake (O’Sullivan et al., 2021; Zhang et al., 2021), impacting both the interpretation of past carbon cycle evolution and future carbon uptake in areas with large aerosol concentrations/surface ozone (e.g. S. Asia/Africa). And, for those models capable, dedicated activities to assess the coupled dynamical response of the Earth System to non-CO_2 gases such as N_2O and CH_4 would provide critical groundwork for their eventual representation in following CMIP activities.

Attribution studies in DAMIP (Gillett et al., 2016) and in general rely on a linking cause and effect; where the cause has historically been interpreted as the change in a climate forcer (concentrations of greenhouse gases, solar or volcanic activity etc), and the effect is some climate impact variable of interest (large scale or regional responses in climate impact variables(Hegerl and Zwiers, 2011), or the probability of some specific event (Naveau et al., 2020)). Hybrid emissions-driven simulations raise the potential for attribution to be defined in terms of actual emissions – arguably a more useful assessment of the linkage between anthropogenic activity and climate impacts. As such, a perspective paper from the attribution community on the framing of attribution studies in emissions-driven simulations would be a valuable addition to the literature.

4.2 Informing multiple lines of evidence

Longer causal chains from emissions-driven simulations may accelerate a shift away from the use of ESM ensembles in assessment from being an ensemble of opportunity used as a proxy for climate uncertainty. We would argue that this transition has already occurred. IPCC reports up to AR5 relied heavily on ESM ensemble distributions as proxies for climate uncertainty. However, IPCC AR6 utilised some specific methodologies (Ribes et al., 2021; Brunner et al., 2020) to reweight ESM distributions of simulations conditional on their historical simulated climate change in the context of observations. These methodologies considered primarily the physical response of the climate system to historical concentrations, and were used to address the assessed 'hot model' bias (Hausfather et al., 2022) in which the CMIP6 distribution contained some models which notably simulated historical warming beyond that seen in observations. A shift to hybrid emissions-driven simulations would introduce an additional source of potential bias in historical concentrations, which would need proper treatment during any assessment. Any weighting scheme would need to properly represent both biases in physical and carbon cycle elements, together with interactions between those elements (multi-variate approaches exist for treating correlated errors(Sanderson et al., 2017b) (such as errors in CO_2 concentrations and global mean temperature).

As the length of the process chain increases, it will become increasingly unlikely that ESMs will simultaneously reproduce the joint historical evolution of emissions, concentrations, and climate response. As such, it might become more useful in assessment to consider ESM ensembles as being sparse samples in a high dimensional complexity space which is illustrative of potential coupled interactions of the Earth System. Such an interpretation pairs well with the use of meta-models (Nicholls et al., 2022) which can be used to interpolate in a higher dimensional response space and filter between global scale projections using observations(Smith et al., 2024).

4.3 Increased computational demand

The operational computational cost of modeling Earth System Processes is a factor in development priorities, but is not prohibitive. The most notable increase in expense (relative to physics-only simulations) in simulating the carbon cycle arises due to the number of tracers required in the biogeochemical models (Kwiatkowski et al. 2014). As such, an ESM configuration requires some tradeoffs between horizontal and vertical resolution, number of tracers and the complexity of chemistry and aerosol representation- with the potential for multiple configurations with comparable computational costs with focus on Earth System processes or resolution respectively (Dunne et al. 2020). However, because for most CMIP-class models, the atmospheric component is significantly more expensive (Danabasoglu et al. 2020; Dunne et al. 2020; Hedemann, Hohenegger, and Ilyina, n.d.), land and ocean biogeochemistry (BGC) can be run in parallel with the atmosphere - somewhat increasing the CPU requirements, but not the overall run-time of the simulation on parallel High Performance Computing (HPC) systems.

Recent ESM development efforts have shown that spinning up oceanic carbon cycles can be achieved on the same timescale as for deep ocean heat content, which is necessary for any atmosphere-ocean coupled configuration (Lindsay et al. 2014; Yool et al. 2020)) (although the exact details of how spinup is achieved can impact residual trends (Séférian et al. 2016)). Moreover, there are a number of promising efforts to accelerate the spinup of the physical ocean (Lindsay 2017; Singh et al. 2022) and land (Lu et al. 2020; Sun et al. 2023), further lowering the technical barriers to contributing with stable interactive carbon configurations. Other efforts have improved the parallelisation of BGC tracers (Linardakis et al. 2022) and grid coarsening (Berthet et al. 2019)- allowing for the better exploitation of HPC infrastructure to run more comprehensive carbon resolving simulations without increases in wallclock time.

Other demands on computation and improvements in model performance for next-generation Earth system models are documented elsewhere and address other key knowledge gaps: the need for kilometer-scale resolution of future climate impacts (Schär et al. 2020), the quantification of parametric uncertainty (Yamazaki et al. 2021), robust sampling of internal variability (Deser et al. 2020) and making best use of machine learning for computational efficiency and for reducing systematic errors in hybrid Earth system models (Eyring et al., 2024)

Some groups have gone further to suggest that climate modeling efforts must pivot to centralized 'digital twins' (Li et al., 2023b) conducted by a small number of modeling centers to provide global simulations at kilometer scale resolution(Bauer et al., 2021). However, such resolutions are not yet tractable in a hybrid emissions-driven configuration, where multi-century simulations are required to spin up the thermal and carbon states of the system. Current highest resolution 3 km 'convection permitting' models achieve 1-10 simulated days per actual day on current High Performance Computing Architecture (Stevens et al., 2019) (forecast models such as IFS (Roberts et al., 2018) use approximations to achieve longer timesteps which allow an order of magnitude higher throughput, but these approximations are debated for climate applications). Hence, we argue that the current 50-100 km resolution 'CMIP' class of climate and Earth system models remain necessary for long term emissions-driven climate projections and should continue as a pillar of climate information in parallel to high resolution activities.

5 Towards comprehensive mitigation modeling in CMIP8 and beyond

There are a number of highly informative model developments that are likely too ambitious for the CMIP7 timeline, but are necessary for a comprehensive process-driven representation of the outcomes of mitigation strategies.

5.1 Closed cycles for water and other major greenhouse gases

Non-CO_2 forcers play a significant role in mitigation dynamics and carbon budget uncertainties, both in terms of forcing and scenario uncertainty (Rogelj et al., 2015). However, the capacity of current generation Earth System Models to produce closed and stable cycles for non-CO_2 greenhouse gases lag behind that of carbon dioxide (Séférian et al., 2020), which has been demonstrated in historical and scenario simulations in CMIP6 (Arora et al., 2020). While interactive treatment methane (Heimann et al., 2020; Folberth et al., 2022) and nitrous oxide (Xu-Ri et al., 2012) are being developed in Earth System Modeling platforms, no models in CMIP6 yet resolved closed cycles for these gases (Séférian et al., 2020). As such - pragmatically, on a timescale of CMIP7, there will remain elements of historical and future simulations which will, for most models, remain exogenously defined but developments could be considered for CMIP8 and beyond (Figure 7d), though it remains likely that some concentration-driven elements will persist – given the large number of minor climate forcers currently handled by SCMs (CFCs, HFCs, PFCs, HCFCs, Halons etc) (Meinshausen et al., 2020).

Closing carbon and nitrogen budgets would require a dedicated joint effort in land and ocean model developments and calibration, and inclusion of potentially absent processes such as lateral transport of dissolved organic carbon and nitrogen (Lauerwald et al., 2017; Lacroix et al., 2021) representation of the coastal ocean dynamics (Mathis et al., 2022), and erosion of coastal permafrost (Nielsen et al., 2022). Similarly, models do not currently close the water cycle. Ice sheets and inland glaciers are a dominant component of sea-level rise (itself perhaps the most critical long term climate adaptation challenge (Hauer et al., 2019)), and yet ESMs do not operationally represent them in coupled simulations. Given this, a number of models have a prioritized focus on including ice sheets and glaciers to "close" the global water cycle (Smith et al., 2021; Lofverstrom et al., 2020).

5.2 Assessment of uncertainty in historical and future land use emissions

A more comprehensive, accurate, and consistently-diagnosed representation of historical land-use emissions and processes is necessary to address both the ensemble bias towards low historical land use emissions as compared to Global Carbon Project estimates in CMIP6 (Friedlingstein et al., 2022b) and the need for a counterfactual no-land-use scenario (Liddicoat et al., 2021). Better land use process representation in an emissions-driven framework, must therefore be supported by diagnostic simulations to map between these accounting systems. In a full transient historical or future simulation, it would be difficult to directly isolate the fraction net land-atmosphere carbon exchange which is associated with land use change and the fraction associated with natural carbon sinks evolving over time under changing climate background states. As such, additional diagnostic counterfactual experiments such as those provided in LUMIP are essential. In CMIP6, these experiments were limited to a concentration-driven framework (e.g. LUMIP experiment *hist-noLu,* a variant of the concentration-driven historical simulation with no land use change).

In the hybrid emissions-driven model, such diagnostic experiments need to be expanded to include emissions-driven experiments to capture the contribution of land use changes to net transient land use fluxes in the coupled simulation. An *esm-hist-noLU,* for example, which followed the protocol of *esm-historical* with fixed land use change, would differ from esm-historical both in terms of the effective land use emissions, but also in terms of any ensuing carbon-climate feedbacks which could modulate the natural emissions also. As such, a full understanding of the role of land use in the transient land sinks in emissions-driven simulations will require a carefully designed set of complementary diagnostic experiments for both historical and future simulations, likely including both emissions-driven and concentration driven diagnostic experiments.

5.3 Process-based representation of carbon removal and storage

The objective to interactively resolve the processes associated with carbon removal within the structural framework of Earth System Models is a key requirement to providing process uncertainty in carbon dioxide removal (Psarras et al., 2017) . Although isolated ESMs have already been used to investigate the potential effectiveness of removals through Bioenergy Carbon Capture and Storage (Muri, 2018; Melnikova et al., 2022; Kato and Yamagata, 2014), or potential oceanic CDR approaches through ocean alkalinization (Fröb et al., 2020) or algal cultivation (Wu et al., 2023), these capacities remain experimental, and lack representations and accounting of sequestered carbon in hybrid emissions-driven simulations.

In cases where ESMs resolve some relevant aspects of the carbon removal process (e.g. BECCS; ocean alkalinization), a pipeline must be created for representing how demand for carbon removal strategies in an IAM scenario is translated into appropriate boundary conditions for the ESM (see Figure 6c/d). Such coupling infrastructure must be urgently defined in order to explore process-based uncertainty in carbon removals in CMIP7.

5.4 Adaptive approaches

The discussion throughout this study has focused on prescribed scenarios, both idealised and quasi-realistic as generated by Integrated Assessment Models in the CMIP ScenarioMIP exercise. In this model, the ensemble of Earth System Models acts as a measure of uncertainty in the coupled carbon-climate response to the emissions pathway. However, the emissions-driven approach opens the door to more interactive treatment of emissions reduction as a function of realised climate change. Since the Paris Agreement, some literature has focussed more on adaptive approaches which allow for convergence of a climate model to a target. Such approaches have been used extensively in simple climate models where it is computationally easy to solve for a given target (Sanderson et al., 2016; Avrutin et al., 2023), and in hybrid mode where simple climate models tuned to reproduce the coupled dynamics of an ESM are used to produce custom emissions pathways for an Earth System Model which are consistent with a given temperature target (Goodwin et al., 2018; Sanderson et al., 2017a; Terhaar et al., 2022). A recent proposal "AERA-MIP" (Silvy et al., 2024) has proposed an interactive adaptive approach, where emissions are adjusted in an Earth System Model simulation using the relationship between cumulative emissions and temperature (Matthews et al., 2009) to interactively compute an emissions trajectory consistent with any prescribed global warming target. Though this approach is a simplistic model for mitigation policy response to experienced climate change, it opens the door for more complex adaptive policy scenarios in the future in which there exist two way couplings between the societal/technological representation. It also allows for emission-driven simulations that can stabilize temperature at various global warming levels, enabling the assessment of impacts at different degrees of warming. Such adaptive approaches are increasingly under consideration in the IAM literature (Gambhir et al., 2023) and some groups have succeeded in partial coupling of an ESM and IAM in an integrated framework.(Collins et al., 2015). Future efforts could explore more fully the interactions between experienced climate impacts, mitigation ambition and capacity.

6 Conclusions

Future climate scenarios have been primarily framed in terms of concentrations (or in terms of metrics of global warming) since the Special Report on Emissions Scenarios (SRES) was introduced (Nakicenovic et al., 2000) at the turn of the 21st century. More recently, a 'parallel process' (Moss et al., 2010) advocated defined concentration pathways, with climate effects conditional on concentration pathways assessed by Earth System Models while Integrated Assessment Models explore scenarios consistent with the pathways. This approach was chosen pragmatically to allow the two communities to work concurrently, and because only a subset of Earth System Models have operationally incorporated interactive and closed carbon cycles. However, this framing does not allow carbon cycle uncertainty as represented by diverse, process-resolving Earth

System Models to be manifested in the scenario outcomes, thus omitting a dominant source of uncertainty in meeting the Paris Agreement (Jones and Friedlingstein, 2020; Holden et al., 2018).

In addition, a rapidly evolving policy landscape increasingly requires information to differentiate between scenarios which represent both different levels of mitigation ambition and different mitigation strategies. A decade earlier in the timing of net-zero CO_2 represents a huge economic investment (Nieto, 2022), but at present we do not have scenario outcomes to clearly illustrate the associated climatic benefits in a way that accounts for all uncertainties. Thus, there is no direct and self-consistent simulation of the benefits of mitigation which can be associated with incremental reductions in emissions. On the implementation side, national mitigation policies that (explicitly or implicitly) rely on land use and carbon dioxide removal (CDR) techniques introduce significant uncertainties which remain unsampled in the current ESM scenario framework.

The utility of ESMs is to a large degree shaped by how they are deployed in model intercomparison projects. For example, it has been argued that ESMs can be made more relevant to climate adaptation challenges by resolving and outputting relevant human and ecosystem climate impacts (Bonan and Doney, 2018). Similarly, with the right experimental design, many existing ESMs already include components that can provide valuable insights into the uncertainty surrounding the timing and implementation of net-zero policies.

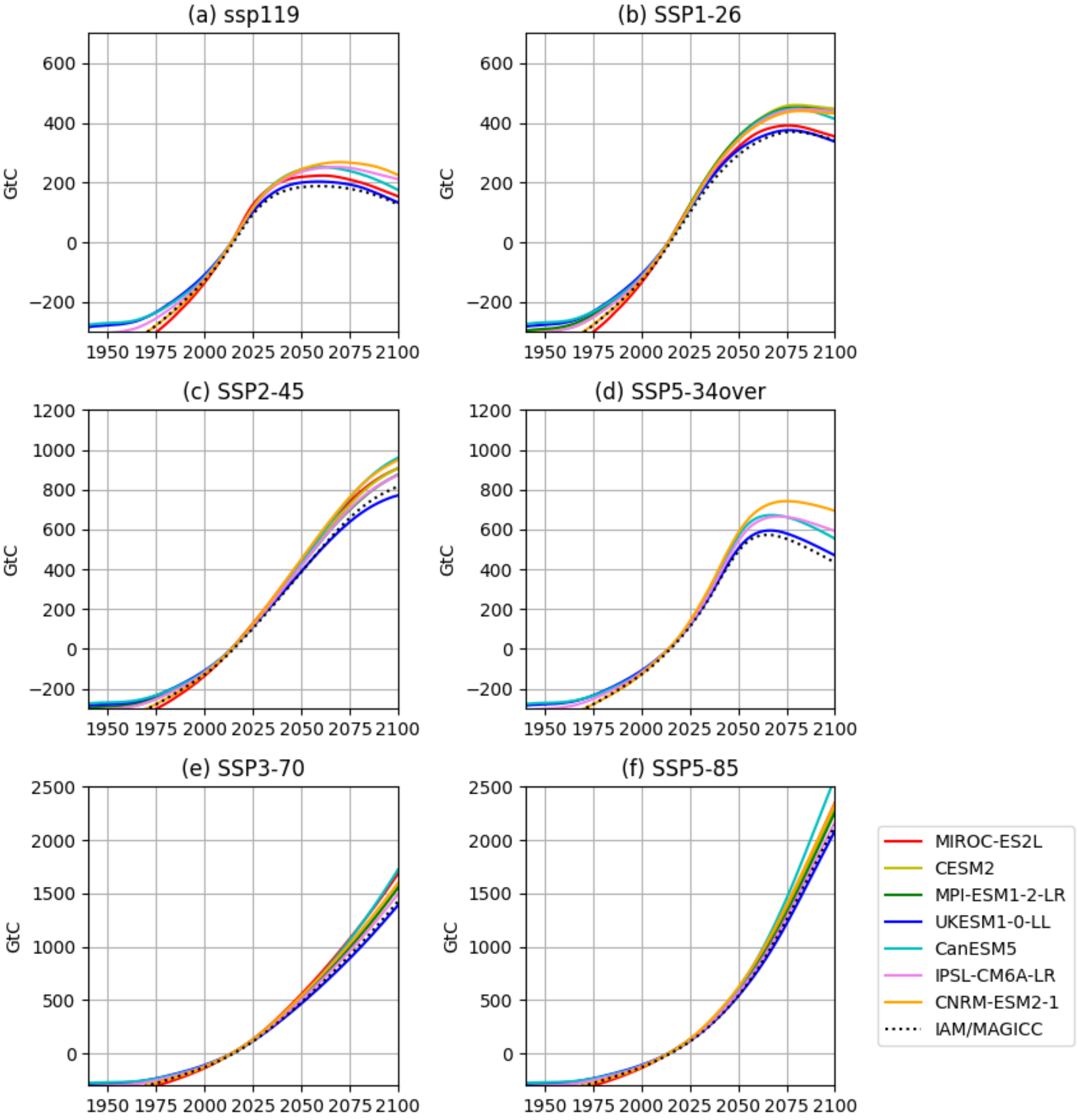
A draft scenario design document for ScenarioMIP CMIP7 indicates a request for a higher fraction of emissions-driven scenarios (The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP7, 2024), and perspectives on the CMIP7 scenario design have called for higher relevance to Paris Agreement objectives through ‘representative emissions pathways’, exploration of CDR risks, and potentially counterfactual scenarios (Meinshausen et al., 2023) while others have called for greater integration into the needs of multiple IPCC working groups and policy relevance (Pirani et al., 2024). Many of these issues can be addressed in a framework enabling an operational assessment of emissions-based policies. This would happen through the explicit representation of carbon dioxide emissions in the context of multiple plausible representations of natural climate system feedbacks. This framework will serve as a structure for incorporating the uncertainties associated with the effectiveness of land use and land and ocean-based CDR techniques as part of a mitigation portfolio, some of which are already implemented in current-generation Earth System Models, and some of which require further development beyond the timescale of CMIP7. This framework needs to be flexible enough to accommodate different models at various stages of development, and different configurations focusing on different elements of the climate problem, necessitating a hybrid approach for CMIP7. We propose that the existing CMIP6 model for accommodating a range of aerosol complexity is extended to the simulation of an emissions and activity-driven carbon cycle. Concentration pathways should still be available for models that require them (and for configurations where carbon cycle feedbacks are not the primary focus, such as high-resolution experiments and some perturbed parameter ensembles). This will need careful communication in the ScenarioMIP framework, as only a subset of models will be subject to carbon cycle uncertainties (though this remains analogous to the CMIP6 treatment of aerosols, where only some models process aerosol emissions directly). It is expected that some climate-relevant forcers such as nitrous oxides and methane will not be represented interactively by a large fraction of models on the timescale of CMIP7, thus exogenous concentrations will still be required in most cases.

Looking ahead to CMIP8 and beyond, ESMs will continue to occupy a critical niche, maximizing the representation of human actions involved in climate mitigation and adaptation in a risk framework which relies on deep and diverse process understanding which is uniquely represented in the collective historical and ongoing effort encapsulated in the CMIP ensemble. Future efforts (and their associated computational expense) should be focused on areas where they can add the most value to understanding the Earth system in an ever-widening ecosystem of simple and complex model configurations which are increasingly well adapted to different aspects of the climate problem.

We argue that a better understanding and representation of emissions-driven dynamics remains one pillar of a wider effort needed to adapt Earth System Models to evolving climate challenges. It has been documented already that there is a need for physically realistic, higher resolution model output (Schär et al., 2020; Bauer et al., 2021), but these must be supplemented by lower resolution operational configurations which are capable of simulating large initial conditional and parametric ensembles of century driven global response to diverse mitigation strategies. Machine learning may also change this tradeoff - approaches are currently being explored to improve the representation of key resolution-dependent physical processes in global climate models (Gentine et al., 2018), with encouraging results. Such approaches also hold great potential for better utilizing observations to inform future improvement of carbon cycle processes in ESMs (Forkel et al., 2019). Bringing together ML developments for both the physical and carbon-cycle components of future emission-driven ESMs offers the potential for a major advance in our ability to model the coupled global climate and carbon cycle (Eyring et al., 2021). However, there remain conceptual problems with overreliance on machine learning for century scale projections where no training data is available (Watson-Parris, 2021).

By requesting that capable centers submit primarily hybrid (i.e. carbon) emissions-driven simulations for CMIP7, the ESM ensemble would become a critically relevant part of the scenario assessment framework, providing the best available process-based estimations of the distribution of potential outcomes resulting from proposed societal transformation pathways. A scenario which achieved a set of policy goals based on the prior generation of models may not achieve those same outcomes with updated models. A default emissions-driven scenario infrastructure would make such comparisons transparent, making it clear when developments in process understanding have measurable impacts on the projected risk associated with a given mitigation strategy.

7 Appendix



825 **Figure A1: cumulative compatible fossil emissions (relative to 2014) for a range of scenarios and Earth System Models in CMIP6, showing MAGICC calculated CO2 emissions from IAM scenarios** (Meinshausen et al., 2020) **(dotted black), and the compatible fossil emissions in CMIP6 ScenarioMIP simulations (colored lines).**

8 Code availability

All code to reproduce Figures in this study is archived at https://zenodo.org/record/8349377. The FaIR simple climate model used to simulate ESM-DECK experiments is available at https://github.com/OMS-NetZero/FAIR

9 Data availability

CMIP6 model output is available through the Earth System Grid Foundation (ESGF). CMIP6 scenario data is available at https://greenhousegases.science.unimelb.edu.au/ and https://tntcat.iiasa.ac.at/SspDb/ .Global Carbon Budget data is available at https://www.icos-cp.eu/science-and-impact/global-carbon-budget/2022

10 Author contribution

BMS wrote the first draft of the paper and produced figures. Additional analysis was carried out by CK. All authors provided input, comments and editing on the various parts of the analysis. In addition, modeling center representatives (JD,VE,CDJ,CJ,DML,RAF,JL,IRS,TI,RS,SZ) were co-responsible for performing subsets of the CMIP6 simulations considered and publishing their model output to the ESGF.

11 Competing Interests

At least one of the (co-)authors is a member of the editorial board of Geoscientific Model Development.

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