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# A Consistent Framework for Uncertainty in Coupled Human-Earth System Models

Jennifer Morris, Andrei Sokolov, Alex Libardoni, Chris Forest, Sergey Paltsev, John Reilly, Adam Schlosser, Ronald Prinn and Henry Jacoby

MIT Joint Program on the Science and Policy of Global Change combines cutting-edge scientific research with independent policy analysis to provide a solid foundation for the public and private decisions needed to mitigate and adapt to unavoidable global environmental changes. Being data-driven, the Joint Program uses extensive Earth system and economic data and models to produce quantitative analysis and predictions of the risks of climate change and the challenges of limiting human influence on the environment—essential knowledge for the international dialogue toward a global response to climate change.

To this end, the Joint Program brings together an interdisciplinary group from two established MIT research centers: the Center for Global Change Science (CGCS) and the Center for Energy and Environmental Policy Research (CEEPR). These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at

Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the program's work lies MIT's Integrated Global System Model. Through this integrated model, the program seeks to discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This report is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

*—Ronald G. Prinn,  
Joint Program Director*

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**Abstract:** Addressing climate change is ultimately a challenge of risk management, which requires an understanding of the likelihood of potential outcomes. We provide integrated, probabilistic socio-economic and climate projections obtained using updated estimates of probability distributions for key parameters in both the human and Earth system components of the MIT Integrated Global System Model (IGSM). The *Reference* scenario results in median end-of-century warming of 3.5°C and a 90% range of 2.8–4.3°C, which is lower than the median of 5.7°C from a prior study using a previous version of the IGSM. About 0.5°C of the difference is due to updated estimates in the human system and the rest of the difference is explained by changes in Earth system estimates. Our results show that climate policy lowers the upper tail of temperature change distributions more than the median, and that even relatively modest policies can significantly reduce the likelihood of high global temperature outcomes. Human system uncertainties contribute more to uncertainty in projected CO<sub>2</sub> concentrations and total radiative forcing, while Earth system uncertainties have the greatest influence on temperature and precipitation. Including additional uncertain inputs does not automatically increase the outcome range because uncertainties can offset one another. Results also show how policy costs can vary greatly among regions. As we improve understanding of underlying technology and economic factors as well as Earth system response to human forcing, further updating of these estimates of uncertainty can make an important contribution to decision-making about mitigation and adaptation.

<b>1. INTRODUCTION</b> .....	<b>2</b>
<b>2. METHOD</b> .....	<b>2</b>
2.1 MODEL.....	2
2.2 MONTE CARLO SIMULATION.....	2
2.3 SCENARIOS.....	4
<b>3. RESULTS</b> .....	<b>5</b>
3.1 EMISSIONS.....	5
3.2 ATMOSPHERIC CO <sub>2</sub> CONCENTRATIONS.....	8
3.3 RADIATIVE FORCING.....	8
3.4 TEMPERATURE.....	9
3.5 PRECIPITATION.....	11
3.6 CONTRIBUTIONS TO OVERALL UNCERTAINTY IN CLIMATE OUTCOMES.....	13
3.7 GDP AND WELFARE EFFECTS.....	14
3.7.1 Global.....	14
3.7.2 Regional Variation.....	16
3.8 ENERGY.....	19
<b>4. CONCLUSIONS</b> .....	<b>20</b>
<b>5. REFERENCES</b> .....	<b>21</b>
<b>APPENDIX A. INPUT PROBABILITY DISTRIBUTIONS</b> .....	<b>24</b>
<b>APPENDIX B. COMPARING EMISSION RESULTS TO EMISSIONS FROM IPCC AR5 REPORT</b> .....	<b>28</b>
<b>APPENDIX C. NEW VS. PREVIOUS WHEELS</b> .....	<b>29</b>

## 1. Introduction

To manage the risks of climate change, information on the likelihood of various outcomes is needed. Many coupled human-Earth system models have been developed to explore potential future energy, emissions, climate and other outcomes of interest. However, uncertainty in these models is often addressed through sensitivity analysis, scenarios and model comparisons. In particular, the Intergovernmental Panel on Climate Change (IPCC) and the broader research community have focused on a defined set of Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs). Uncertainty in human and Earth system outputs is often represented as the ranges resulting from model comparisons focused on SSPs and RCPs (e.g. IPCC, 2014; Riahi *et al.*, 2017; Rogelj *et al.*, 2018; WCRP, 2011; Eyring *et al.*, 2016). While these exercises can provide useful insights, they limit the uncertainty space explored (e.g. by focusing on a limited set of defined socioeconomic pathways) and provide no quantitative probabilistic interpretation. This leaves decision-makers and other users of these scenarios to make their own judgments about likelihoods, and those judgements vary greatly based on the individual's interest and level of understanding. There are growing calls for more formal probabilistic, risk-based approaches to inform discussions about mitigation and adaptation (e.g. CBO, 2005; Hausfather and Peters, 2020).

Formal uncertainty studies of global economic development, emissions and climate in the literature are now quite dated, and typically focus on a limited set of uncertainties (e.g. Reilly, *et al.* 1987; Peck and Teisberg, 1993; Nordhaus and Popp, 1997; Pizer, 1999; Webster, *et al.*, 2002; Baker, 2005; Hope, 2006; Nordhaus, 2008; Sokolov, *et al.*, 2009; Webster *et al.*, 2012, Anthoff and Tol, 2013; Lemoine and McJeon, 2013). The economic outlook, technology costs, and estimates of Earth system response have changed considerably over the past decade with new data, analysis and evidence, making it useful to revisit these uncertainties. Many authors continue to use the IPCC 8.5 W/m<sup>2</sup> scenario (RCP8.5) as a reference “no policy” baseline, but given slower economic growth, falling costs of low-carbon energy options and government interventions worldwide directed at expanding the role of renewables, many now believe the RCP8.5 “no policy” scenario to be highly unlikely (Mager *et al.*, 2017; Hausfather and Peters, 2020; Grant *et al.*, 2020; Morris *et al.*, 2020). Gillingham, *et al.*, (2018) is a more up-to-date multi-model uncertainty study, but it focuses on only two uncertain socio-economic variables—population and economic growth.

This study takes a probabilistic ensemble approach to representing a comprehensive set of both socio-economic and climate uncertainties. Our goal is to develop updated probability distributions of human and Earth system outcomes

that can serve as a basis for risk-based decision-making. This study advances an approach used by Webster, *et al.* (2002; 2003; 2012) and Sokolov, *et al.* (2009), employing an updated and improved version of the MIT Integrated Global System Model (IGSM) and a significant reassessment of uncertainty in input parameters. The resulting integrated, probabilistic socio-economic and climate projections provide insight into the probability of outcomes of interest, including emissions, CO<sub>2</sub> concentrations, temperature, precipitation, Gross Domestic Product (GDP) and energy use.

In this paper, Section 2 describes the model, method and scenarios employed, Section 3 presents the resulting distributions for key outcomes and Section 4 provides conclusions.

## 2. Method

### 2.1 Model

Coupled human-Earth system models allow for consideration of both socio-economic and climate uncertainties. Here we use the MIT IGSM framework, which links the Economic Projection and Policy Analysis (EPPA) model to the MIT Earth System Model (MESM). EPPA is a recursive-dynamic multi-sector, multi-region computable general equilibrium (CGE) model of the world economy (Chen *et al.*, 2016; Paltsev *et al.*, 2005). It is designed to develop projections of economic growth, energy transitions and anthropogenic emissions of greenhouse gas and air pollutants. The model projects economic variables (GDP, energy use, sectoral output, consumption, prices, etc.) and emissions of long-lived greenhouse gases (CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O, HFCs, PFCs and SF<sub>6</sub>) and short-lived air pollutants (CO, volatile organic compounds (VOCs), NO<sub>x</sub>, SO<sub>2</sub>, NH<sub>3</sub>, and black carbon and organic carbon aerosols) from combustion of carbon-based fuels, industrial processes, waste handling, agricultural activities and land use change. MESM is an Earth system model of intermediate complexity, modeling the Earth's physical, chemical and biological systems to project environmental conditions that result from human activity. MESM is able to project the full spectrum of climate-relevant conditions across the Earth system, including atmospheric concentrations of greenhouse gases and aerosols, temperature, precipitation, ice and snow extent, sea level, ocean acidity and temperature among other variables (Sokolov, *et al.*, 2018). By linking these models, the IGSM also allows for the development of emissions pathways consistent with different 21<sup>st</sup> century temperature outcomes.

### 2.2 Monte Carlo Simulation

Following the approach used in Webster *et al.* (2012; 2003) and Sokolov *et al.* (2009), we employ Monte Carlo uncertainty analysis. The basic steps are: (1) identify uncertain input parameters and develop probability distributions for them, (2) sample from the distributions to construct

multiple sets of parameter values, and (3) simulate large ensembles of model runs using the sampled parameter values. The distribution of model outcomes from the ensemble of simulations provides estimates of future states and their uncertainty, conditional on the model structure, the distributions of uncertain input parameters, and the assumed scenario settings. **Figure 1** depicts this approach for representing uncertainty in a coupled human-Earth system model (the MIT IGSM), creating probabilistic, internally consistent, integrated socio-economic and climate projections.

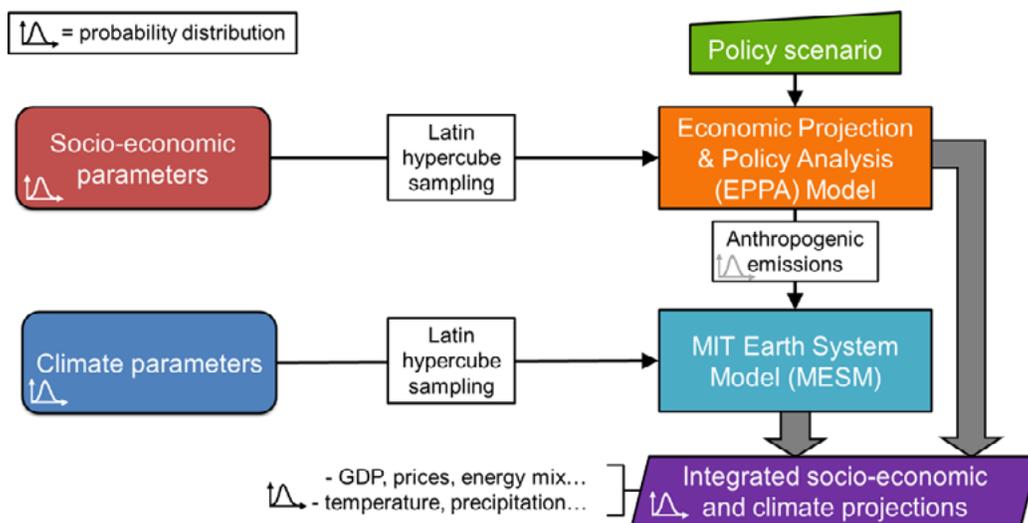
In this particular approach, climatic and other environmental feedbacks on the economic system that would result from changes in the Earth system are not included. The development of probability distributions for socio-economic parameters is described in Morris *et al.*, (2021) and for Earth system parameters in Libardoni *et al.*, (2019, 2018a,b). Estimated distributions for socioeconomic parameters were based on statistical estimates using historical data where possible (e.g. GDP growth, autonomous energy efficiency improvement, rate of technology penetration), published estimates of uncertainty (e.g. population, fossil resource availability), literature results and expert judgement (e.g. future technology costs, elasticities of substitution, urban pollutant initial inventories and trends, capital vintaging). Probability distributions are constructed for each socio-economic parameter, some by region or sector, creating a total of over 150 distributions. For a subset of related parameters, correlation structures are also imposed.

Uncertain Earth system parameters were estimated using an optimal fingerprint approach (i.e. Libardoni *et al.*, 2019, 2018a,b). This method uses historical data on surface climate, ocean heat content, and concentrations of greenhouse-relevant gases and aerosols to estimate a joint distribution of parameters representing climate sensitivity,

ocean heat uptake and aerosol radiative forcing. These estimates are based on observations through 2010, whereas previous estimates (Forest *et al.*, 2008) used data only up to 1995. We also account for uncertainty in the carbon uptake by the ocean and terrestrial ecosystems (Sokolov *et al.*, 2018). A summary of the probability distributions for all uncertain parameters, both socio-economic and Earth system, is provided in Appendix A.

To reduce computational requirements when conducting Monte Carlo analysis with the relatively complex IGSM, we employ Latin Hypercube sampling (LHS) (McKay *et al.*, 1979; Iman and Helton, 1988). LHS divides the distribution for each variable into equal probability segments. The mid-point values for each segment of each variable are chosen randomly, without replacement. Each random selection across all variables creates one ensemble member. The process generates an ensemble size equal to the number of probability segments. This sampling strategy assures that every equally likely segment of the distribution, including segments in the distribution tails, is sampled exactly once. We use 400-member ensembles, shown to adequately approximate the limiting distribution when using LHS, whereas pure random sampling often requires thousands or tens of thousands of samples to achieve similar accuracy (Webster *et al.*, 2012).

The same set of 400 samples is used for a reference scenario and a set of climate policy scenarios (described below). Pairwise comparisons of results are made across scenarios with identical input values for each ensemble member pair, with the only difference between the two being the introduction of a policy constraint. This procedure is designed to estimate policy costs, defined as the difference between simulated macroeconomic welfare in a policy case and that in the reference case for each ensemble member.



**Figure 1.** Approach for representing uncertainty in a coupled human-Earth system model (MIT IGSM) and creating probabilistic, internally consistent, integrated socio-economic and climate projections.

## 2.3 Scenarios

Climate policy is treated as a deep uncertainty, explored through a set of ensemble scenarios, rather than attempting to assign a subjective probability distribution to policy measures. The ensemble scenarios include a reference case, a case extrapolating Nationally Determined Contributions (NDC) targets of the Paris Agreement, and policy cases that achieve long-term temperature stabilization targets of 2°C and 1.5°C (Table 1). Morris *et al.* (2021) explore the same set of scenarios (labeled by their median temperature outcomes), focusing on technology and socio-economic outcomes. The *Reference* case does not include the mitigation pledges made by the countries in their submissions under the Paris Agreement, but it does include policies targeting an expansion of renewables in power generation consistent with IEA (2017). Climate and energy policies have also been responsible for reducing the costs of low-carbon technologies and otherwise shaping energy consumption patterns through building standards and codes, appliance and vehicle efficiency and other policies. While not explicitly represented, the effects of these efforts are reflected in lower renewable technology costs and a slowing rate of emissions growth over the last decade.

The *ParisForever* scenario assumes the NDCs submitted under the Paris Agreement are met by all countries by 2030 and retained thereafter (Reilly *et al.*, 2018). For countries with absolute NDC targets (e.g. emission reductions relative to a historic year), those targets are retained through the horizon of the simulation, keeping emissions flat after 2030. Countries with NDC targets that are relative to business-as-usual (BAU) emissions, or are in terms of emissions intensity, retain those targets through the horizon of the simulation, but since BAU emissions and GDP vary, the targets result in varying emissions for those regions (and the world total) across ensemble members.

The *Paris2C* and *Paris1.5C* scenarios are designed to achieve the long-term temperature stabilization targets of the Paris Agreement. The Paris Agreement has the long-term goal

of “holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels (UNFCCC, 2015).” We use the period 1861–1880 to determine preindustrial temperature. We interpret “well below” as targeting an emissions level so that the global mean surface temperature is likely to remain below 2°C. In IPCC terminology, “likely” is quantified as a 2/3 (66%) chance of occurring (Mastrandrea, *et al* 2010). We interpret the 1.5°C aim as the median result, achieving it with a 50% likelihood. For both scenarios, we assume all countries meet their NDCs by 2030, after which a global price, designed to achieve the long-term targets, is applied to all greenhouse gases, sectors and regions. Under median values of socio-economic parameters in the EPPA model and our estimates of climate uncertainty, the global emissions trajectories result in a 66% likelihood of remaining below 2°C (*Paris2C*) above pre-industrial levels or a 50% likelihood of remaining below 1.5°C (*Paris1.5C*) above pre-industrial levels.<sup>1</sup> The resulting regional emissions trajectories are then implemented as emissions caps with trading among sectors, regions and greenhouse gases, and

<sup>1</sup> There are many alternative trajectories that could also achieve the same outcomes (66% chance of 2°C or 50% chance of 1.5°C). For the particular paths used here, we first found an initial GHG emissions price that, when beginning in 2035 and rising at 4% per year under median values of socio-economic parameters, would achieve the temperature target with the specified probability given the uncertainty in our climate parameters. Such an optimized global emissions price policy tends to have a dramatic reduction in emissions in early years of the policy. For the *Paris2C* scenario, we smoothed the global emissions trajectory in early years, while maintaining the same cumulative GHG budget consistent with the temperature target, and then implemented that path as an emissions cap, requiring each ensemble member to achieve the same global emissions trajectory. For the *Paris1.5C* scenario, there is not room in the GHG budget to smooth the early years of the emissions trajectory without employing negative emissions in later years, which we do not include. So for *Paris1.5C*, the emissions path resulting from the global emissions price policy is implemented as an emissions cap for the ensemble.

**Table 1.** Scenarios used for ensembles

Scenario	Description	Median Global Temperature Outcome <sup>a</sup>
<i>Reference</i>	No Paris Agreement targets, but expansion of renewables policies	3.5°C
<i>ParisForever</i>	Paris Nationally Determined Contribution (NDC) targets are met by all countries by 2030 and retained thereafter	3.1°C
<i>Paris2C</i>	Paris NDC targets are met by all countries by 2030, after which there is an emissions cap, implemented with a global emissions price, ensuring 2100 global surface mean temperature does not exceed 2°C above pre-industrial levels with a 66% probability	1.9°C
<i>Paris1.5C</i>	Paris NDC targets are met by all countries by 2030, after which there is an emissions cap, implemented with a global emissions price, ensuring 2100 global surface mean temperature does not exceed 1.5°C above pre-industrial levels with a 50% probability	1.5°C

<sup>a</sup> Average global surface air temperature in 2091–2100 relative to 1861–1880.

therefore a global emissions price. The emissions caps are binding upper limits on emissions, and assure that the global emissions path determined under median values of socioeconomic inputs are also met when inputs are uncertain. Under the emissions caps with median parameter settings, there is no emissions trading among regions, as the marginal cost of abatement across regions is already equalized. However, trading will occur as socio-economic uncertainty within the ensembles is sampled.

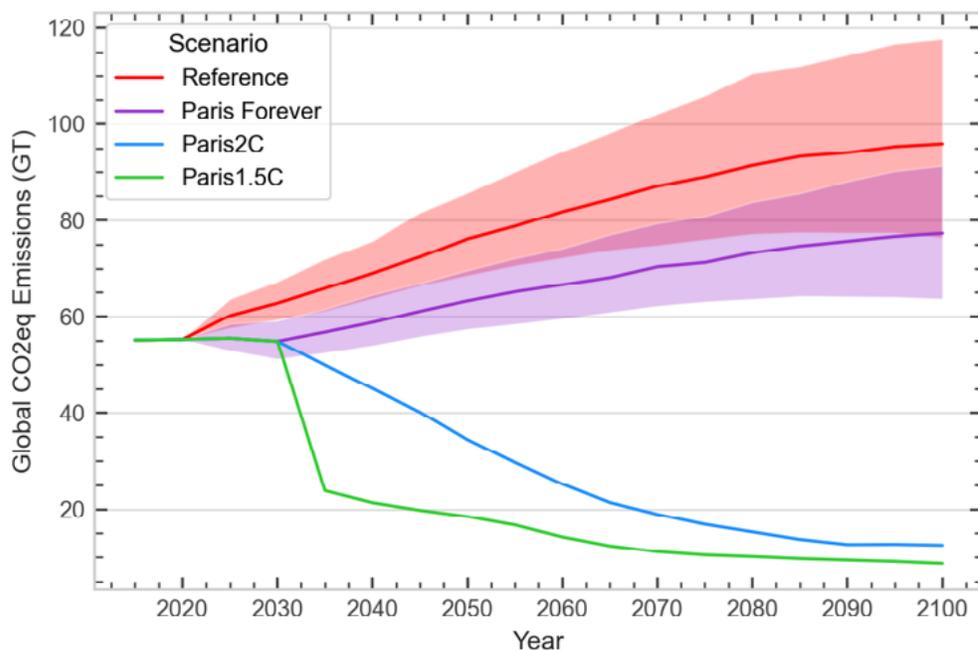
### 3. Results

#### 3.1 Emissions

The *Reference* scenario has the greatest uncertainty, with GHG emissions in 2100 ranging from about 76 to 118 gigatonnes of CO<sub>2</sub>-equivalent (Gt CO<sub>2</sub>eq) in 2100 (5<sup>th</sup> to 95<sup>th</sup> percentile), with a median of 96 Gt (**Figure 2**). Compared to previous analyses (e.g. Webster *et al.*, 2012), this range is narrower. This difference is driven by updates to the input probability distributions as well as updates to the EPPA model. Changes relative to the version used in Webster *et al.* (2012) include slower regional economic growth, lower costs of low-carbon energy options, government interventions worldwide directed at expanding the role of renewables, and a myriad of energy policies implicitly included through calibrating the EPPA model's historical emissions path to historical data. These revisions all lower the high end of emissions. In particular, the GDP growth prospects for China have slowed considerably, resulting in

lower emissions. China is the largest CO<sub>2</sub> emitting economy in the world and so this change alone significantly reduces the upper bound of global emissions. The *Reference* scenario also now includes expansion targets for renewables consistent with projections from the International Energy Agency (IEA, 2017), which also reduces the upper bound of global emissions. Further, the emissions variability in some countries/regions tend to offset each other, lowering variability at the global level.

The policy scenarios reduce or eliminate emissions uncertainty. The 90<sup>th</sup> percentile range for *ParisForever* emissions is 64–91 Gt CO<sub>2</sub>eq, with a median of 77 Gt. As previously noted, NDC targets specified as reductions from reference or specified as emissions intensity goals leave room for uncertainty in emissions projections. In 2100, median emissions in *ParisForever* are about 19% lower than median 2100 emissions in *Reference*. Year 2100 emissions in *Paris2C* and *Paris1.5C* are 13 Gt and 9 Gt, respectively, which is 87% and 91% below median 2100 *Reference* emissions. In principle, the emissions constraints could be non-binding leading to emissions uncertainty (with some ensemble members that might have emissions below the constraint). In practice, however, the constraints are binding in all cases, so there is no uncertainty in global emissions in the *Paris2C* and *Paris1.5C* policy ensembles. Ensemble members do, however, differ in terms of regional and sectoral emissions and emissions of individual greenhouse gases. For cumulative emissions over the period of 2025–2100, the *ParisForever* median is 18% lower than the *Reference*



**Figure 2.** Global greenhouse gas emissions over time for each ensemble scenario. Shaded areas represent 90% probability bounds. Lines are the medians.

median, *Paris2C* is 65% lower, and *Paris1.5C* is 76% lower. See Appendix B for a comparison of emissions results from these scenarios to those from the IPCC Fifth Assessment Report (IPCC, 2014).

Many of the models and scenarios used by the IPCC (2018; 2014) employ negative emission technologies, such as biomass electricity with carbon capture and storage (BECCS) or direct air capture (DAC). There are many questions about the cost of technologies, their ability to operate at scale, sustainably, and in a way that makes them publicly acceptable. Because the economics of these advanced options are so uncertain, as is the scale of use even if economic and technological challenges are overcome, we did not include them in any of our ensembles. As a result, the *Paris2C* and *Paris1.5C* targets are met without negative emission technologies. In other work, that includes BECCS in the MIT EPPA model, the technology dominates once it is competitive, effectively capping the carbon price, reducing policy costs, and allowing fossil energy use to continue (Fajardy *et al.*, 2020). The ensembles also do not consider mitigation through changing land use, such as through afforestation, to achieve emission targets. These, too, would lower the economic cost and carbon price and provide more headroom for other GHG emissions (Reilly *et al.*, 2018).

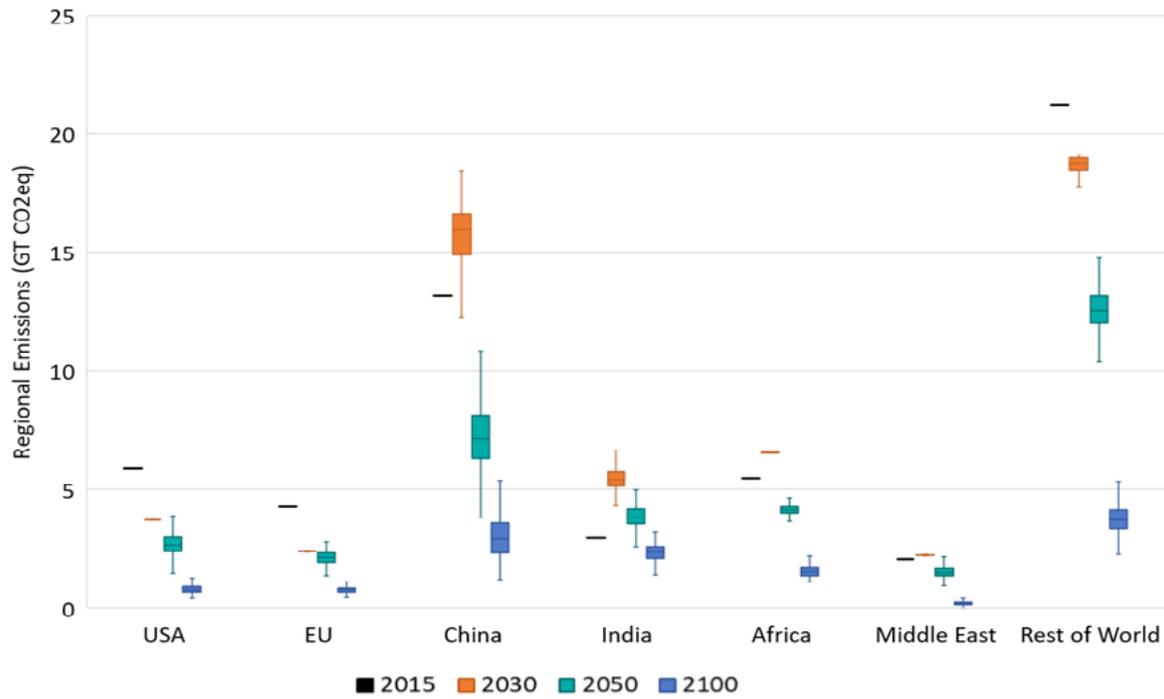
There is a presumption in many policy circles that there is a need to get to net zero emissions in this century, possibly as early as 2050, and this then requires a negative emission technology in order to offset hard-to-abate emissions, such as methane from rice and ruminants, and nitrous oxide from soil management. However, all of our ensemble members meet the emissions constraints imposed in the *Paris2C* and *Paris1.5C* ensembles without negative emissions or net zero emissions. As emphasized in the IPCC, at least as a first approximation, it is the cumulative budget over the century that matters for temperature outcomes (see, e.g. Rogelj *et al.* (2019)). Net zero or negative emissions in the latter half of the century would provide more near-term headroom, allowing for a more gradual transition from the current fossil fuel heavy energy system, and lower near-term costs. In particular, to meet the *Paris1.5C* emissions target under our formulation (without negative emissions options) requires an almost 60% drop in emissions between 2030 and 2035, which results in very high costs, even in early years as much more abatement is needed early to balance out emissions in the 2<sup>nd</sup> half of the century.

The carbon budgets for the *Paris2C* and *Paris1.5C* scenarios are somewhat larger than estimates for these temperature targets presented in the IPCC Special 1.5°C Report (e.g., IPCC, 2018; Rogelj *et al.*, 2018). For the set of climate parameters used in this study, the median transient climate response to (cumulative carbon) emissions (TCRE) obtained in our ensembles of MESM simulations is nearly identical to the value used in the IPCC Special 1.5°C Report

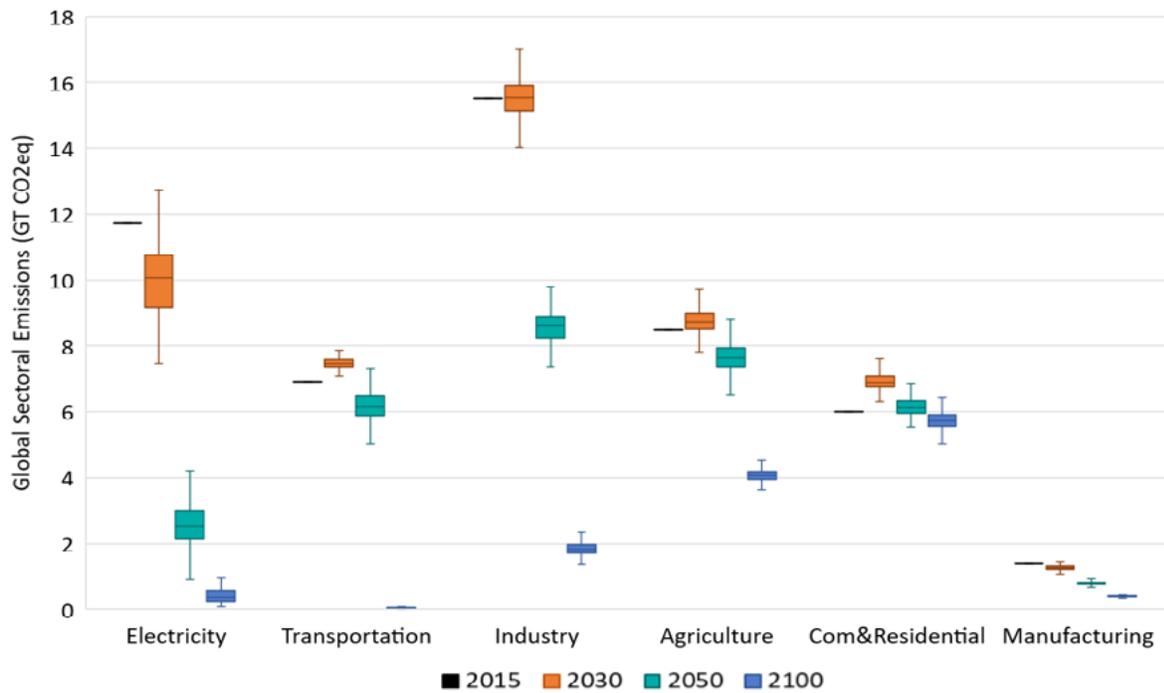
(IPCC, 2018), but the 90% probability range of the TCRE is narrower. As a result, the CO<sub>2</sub>-only carbon budget for achieving a given target with 50% probability as simulated by MESM will be similar to that shown by IPCC Special 1.5°C Report (Forster *et al.*, 2018), while the allowable budget for the 33%/66% probability will be lower/higher. However, the main reason for the difference in carbon budget is the smaller temperature change associated with non-CO<sub>2</sub> forcing. Compared with most IPCC scenarios, we have lower non-CO<sub>2</sub> GHG emissions allowing for more CO<sub>2</sub> emissions, and somewhat higher SO<sub>2</sub> emissions resulting in greater negative aerosol forcing. Our carbon emissions (relative to 2017) are near the high end of the range reported by Rogelj *et al.* (2019).

Although all ensemble members in the *Paris2C* and *Paris1.5C* scenarios must meet the same global emissions trajectory (see Figure 2), there is uncertainty about how those emissions are distributed across regions and sectors since emissions trading is allowed. The regional and sectoral distributions depend on the cost of abatement opportunities, which change with different values of input parameters. To demonstrate this feature of the results, **Figures 3 and 4** show the uncertainty in emissions for a set of regions and sectors in 2030, 2050 and 2100 in the *Paris2C* scenario, along with 2015 emissions as a point of reference. Uncertainty in these figures is represented as box plots: the boxes are the interquartile range (25<sup>th</sup>-75<sup>th</sup> percentile) and the whiskers extend to 1.5 times the interquartile range. The greatest variance in regional emissions is in China and the “Rest of World” (all other regions combined). Uncertainty in emissions in 2030 exists for regions with Paris NDC targets related to BAU emissions or emissions intensity. Beyond 2030, all regions must reduce their emissions, with each region’s ultimate level of reductions depending on abatement costs in the region.

The greatest variance in sectoral emissions is in electricity and industry. The sectoral results also suggest that there are limited abatement opportunities in the agriculture, commercial and residential, and industry sectors. This partly reflects real decarbonization challenges in those sectors. However, it also reflects the model structure—if additional low-carbon technological options for those sectors were represented in the model, those sectors likely would achieve further emissions reductions, depending on the cost of the options and the stringency of the policy. This analysis thus helps to identify areas where the model would benefit from additional research and model development related to non-energy sector mitigation options. Representation of additional options would also impact policy cost uncertainty.



**Figure 3.** Boxplots of regional GHG emissions in 2030, 2050 and 2100 in selected regions. The 2015 emissions are shown in black as a point of reference.



**Figure 4.** Boxplots of global sectoral GHG emissions in 2030, 2050 and 2100. The 2015 emissions are shown in black as a point of reference.

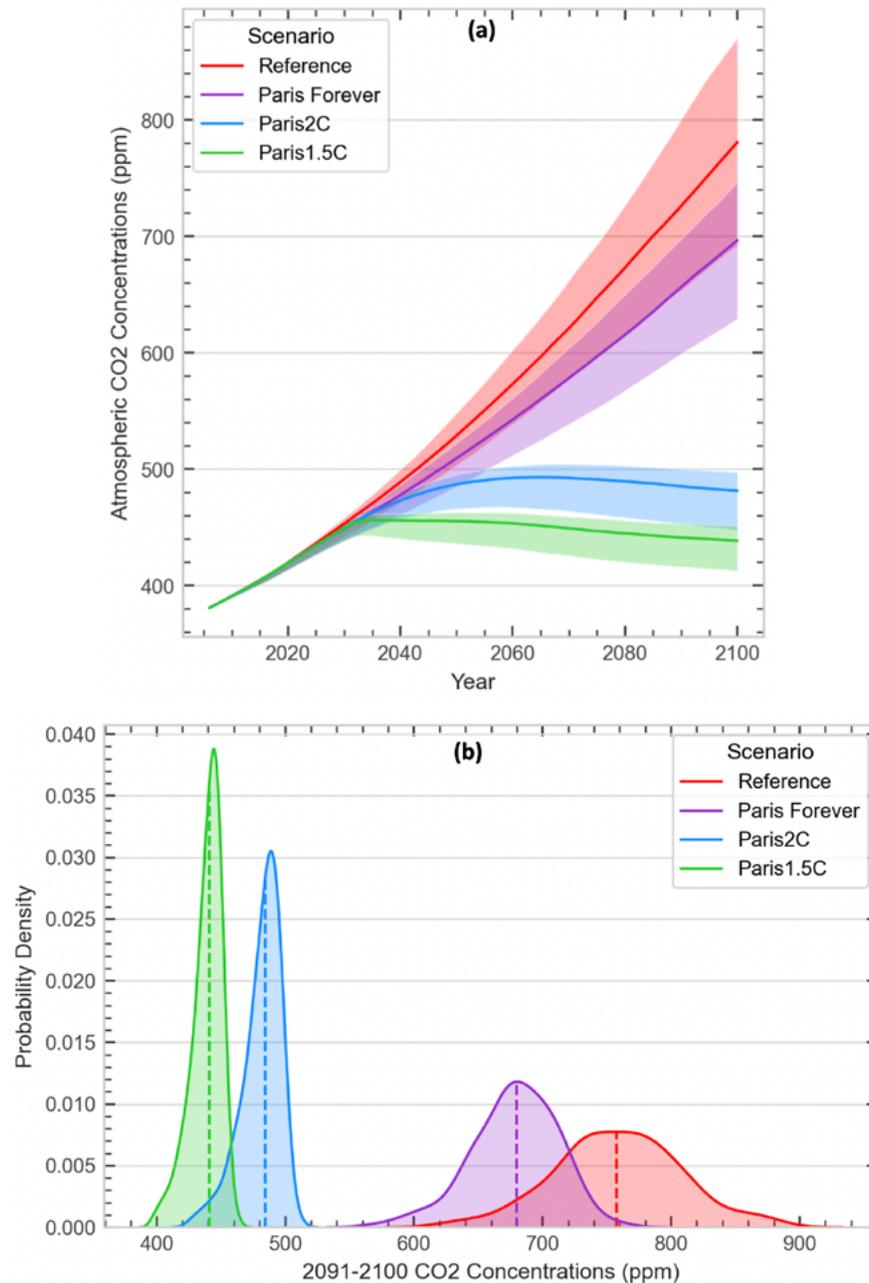
### 3.2 Atmospheric CO<sub>2</sub> Concentrations

The *Paris2C* and *Paris1.5C* scenarios have a smaller 90% range of CO<sub>2</sub> concentrations over the entire 2020 to 2100 period than the *Reference* and *ParisForever* scenarios due to their fixed emissions constraints (**Figure 5a**). The driver of uncertainty in CO<sub>2</sub> concentrations under those scenarios is the rate of carbon uptake by the ocean and terrestrial ecosystems. When emissions are also uncertain, the range of concentrations is wider, with the *Reference* scenario having the widest range. Moving from *Reference* to *ParisForever* to

*Paris2C*, the distributions of end-of-century concentrations become increasingly asymmetric, with policy trimming the upper tail more than the lower tail (**Figure 5b**). *Paris1.5C* is slightly less skewed than *Paris2C*. The 90% bounds are 678–845 ppm for *Reference*, 618–727 ppm for *ParisForever*, 451–500 ppm for *Paris2C* and 415–453 ppm for *Paris1.5C*.

### 3.3 Radiative Forcing

By the end of the century, total radiative forcing, which is the sum of the effects of all long-lived greenhouse gases



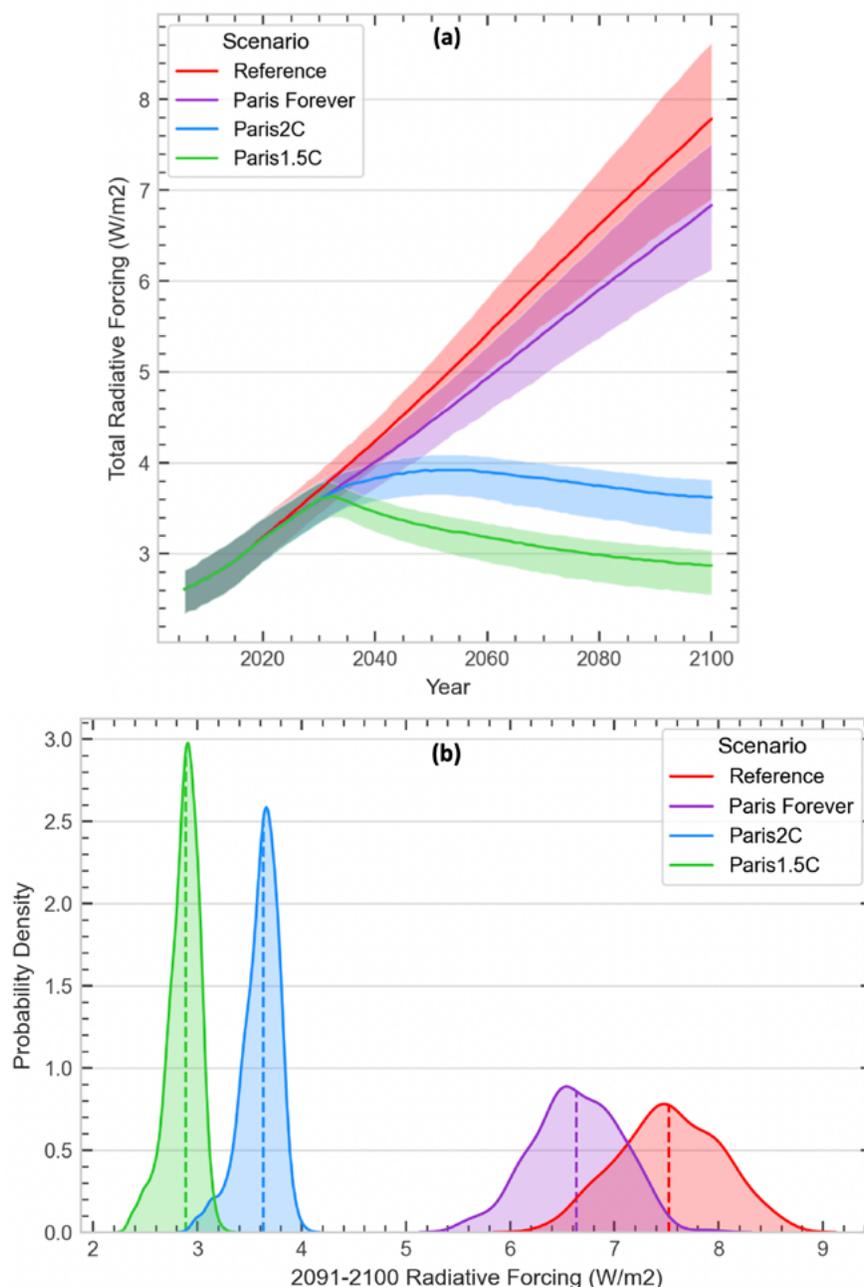
**Figure 5.** (a) CO<sub>2</sub> Concentrations over time for each ensemble scenario (shaded areas represent 90% probability bounds. Lines are the median). (b) Frequency distributions of CO<sub>2</sub> Concentrations in 2091–2100.

plus tropospheric ozone and aerosols, has a 90% range of 6.7–8.3 W/m<sup>2</sup> for *Reference*, 6.0–7.3 W/m<sup>2</sup> for *ParisForever*, 3.3–3.8 W/m<sup>2</sup> for *Paris2C* and 2.6–3.1 W/m<sup>2</sup> for *Paris1.5C* (**Figure 6a**). The uncertainty in radiative forcing is driven by: (1) varying concentrations due to Earth system feedback (as shown above), and (2) uncertainty in the strength of sulfates aerosol forcing. Similar to the CO<sub>2</sub> concentrations, with policy the upper tails of the distributions are trimmed more than the lower tails (**Figure 6b**).

### 3.4 Temperature

At the end of the century, the median 2091–2100 temperature change relative to pre-industrial levels (1861–1880) is 3.5°C for *Reference*, 3.1°C for *ParisForever*, 1.9°C for *Paris2C* and 1.5°C for *Paris1.5C* (**Figure 7**). The 90% range is 2.8–4.3°C for *Reference*, 2.4–3.8°C for *ParisForever*, 1.5–2.3°C for *Paris2C* and 1.2–1.9°C for *Paris1.5C*.

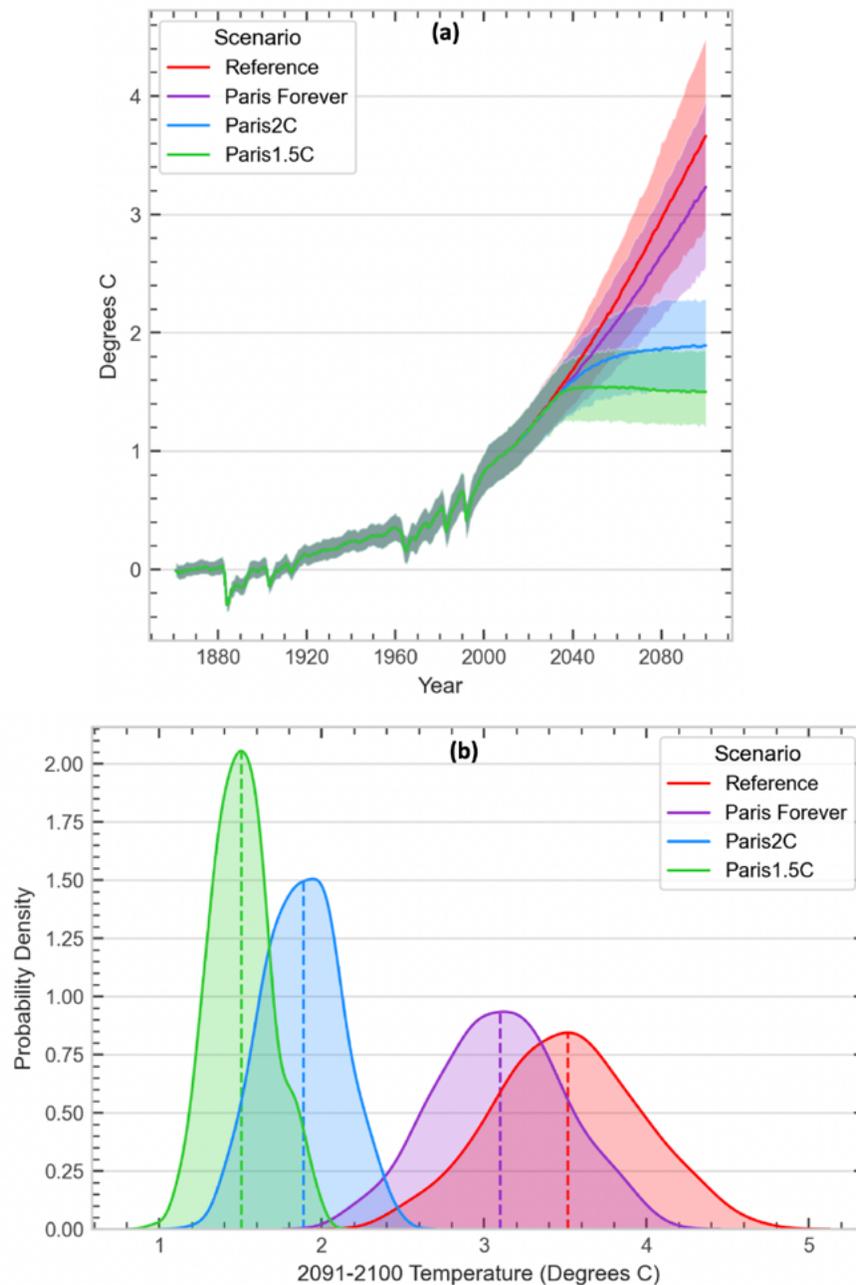
The surface warming projected in this study for the *Reference* emissions scenario is significantly lower than estimates



**Figure 6.** (a) Total radiative forcing over time for each ensemble scenario relative to 1861–1880 (shaded areas represent 90% probability bounds. Lines are the medians). (b) Frequency distributions of total radiative forcing in 2091–2100 relative to 1861–1880 (dashed lines are the medians).

obtained in previous studies using earlier versions of the MIT IGSM (Sokolov *et al.*, 2009; Webster *et al.*, 2012). In these earlier studies, ensemble simulations with reference emissions from Webster *et al.*, (2008) and climate parameter distributions from Forest *et al.*, (2008) showed median warmings of 5.7°C, relative to the 1861–1880 mean. Ensemble simulations with the new climate parameter distributions and MESM version used in this study and the old reference emissions from Webster *et al.*, (2008) produced

median warming of 4.0°C relative to the 1861–1880 mean. This indicates that of the difference in reference median surface warming results between this study (3.5°C) and the previous studies (5.7°C), 0.5°C can be explained by the difference in anthropogenic emissions, and the remaining difference is due to differences in the climate system response to emissions. Sokolov *et al.*, (2009) also reported a strong dependency of the projected warming on the climate parameter assumptions. Namely, simulations with



**Figure 7.** (a) Global average surface air temperature over time for each ensemble scenario relative to 1861–1880 (shaded areas represent 90% probability bounds. Lines are the median). (b) Frequency distributions of global average surface air temperature in 2091–2100 relative to 1861–1880 (dashed lines are the medians).

an alternative distribution of climate parameters, calculated using different data sets for changes in deep-ocean heat content, produced median surface warming of only about 4.5°C relative to the 1861–1880 mean. For additional details on the difference between this study and the previous studies, see Appendix C.

Importantly, climate policy lowers the upper tail of the temperature change distributions more than the median. For example, comparing *Paris2C* to the *Reference*, the median temperature is reduced by 1.6°C (from 3.5°C to 1.9°C) and the 95<sup>th</sup> percentile is reduced by 2°C (from 4.3°C to 2.3°C). This illustrates that one of the greatest roles of climate policy is to lower (or eliminate) the likelihood of extreme temperature outcomes, particularly when policy is formulated as an absolute cap on emissions in many regions. This is highlighted in **Table 2**, which shows how the percentage of runs exceeding given temperature levels varies across the ensemble scenarios. Results indicate that even relatively modest policies can significantly reduce the likelihood of high temperature outcomes. For example, the *ParisForever* scenario has modest emissions reductions relative to the *Reference*, yet greatly reduces the chance of temperature changes above 4°C (decreasing it from 15% to <0.25%). The *Paris2C* scenario essentially bounds temperature to 2.5°C, with less than 0.25% of runs exceeding that level. The *Paris1.5C* scenario essentially bounds temperature to 2°C, with less than 0.25% of runs exceeding that level. Also important are the lower tails of the temperature change distributions. As seen in Figure 7b, under *Reference* and *ParisForever*, the 2°C temperature target is essentially out of reach.

Another important insight from these results is that, due to uncertainties in the climate system, a given emissions constraint cannot guarantee that a particular temperature target is met. Here we have designed emissions trajectories (*Paris2C* and *Paris1.5C*) to achieve a particular temperature target (2°C or 1.5°C) with a given probability (66% or 50%),

accounting for our estimated climate system uncertainty, meaning there is still significant probability (33%-50%) that the temperature targets will be exceeded. Looked at in another way, depending on how Earth system uncertainties are resolved, we may find that we can allow somewhat higher emissions (with low climate response) or will need to cut emissions more deeply (with high climate response) if indeed we want to remain below a given temperature target. One implication of these results is that emissions targets intended to achieve specific temperature goals would need to be adjusted over time as the uncertainty in the climate system is resolved.

To communicate these results to a broader audience, we have found it useful to convert the distributions into roulette wheels characterizing the chance of a result within various temperature intervals (e.g. Prinn, 2012; **Figure 8**). We have called these “Greenhouse Gamble Wheels.” Any of the results can be represented in such a “wheels” format, and further work can downscale global into regionalized results using hybrid methods (e.g. Schlosser *et al.* 2020, Schlosser and Strzepek 2015, Schlosser *et al.*, 2012).

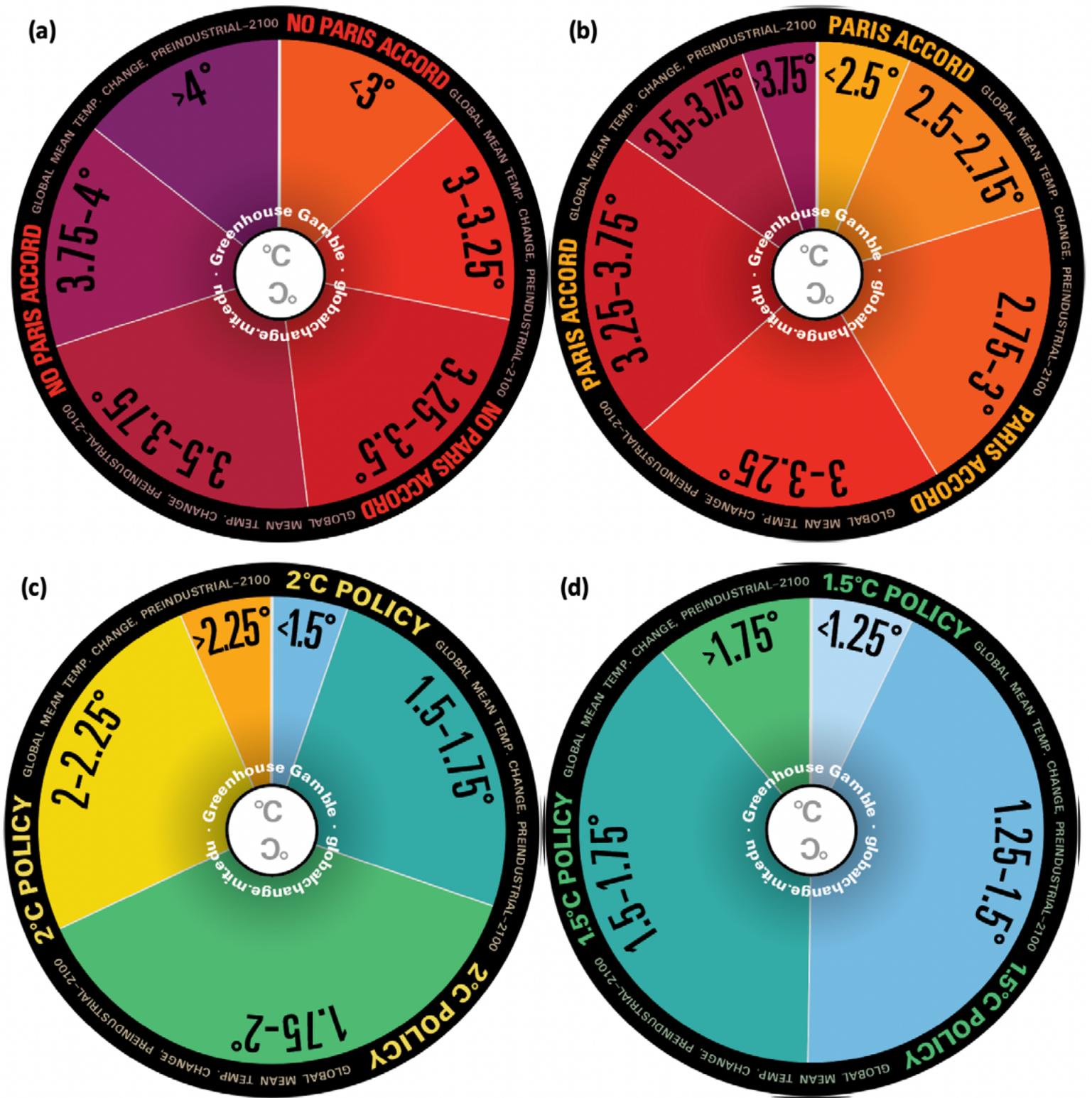
### 3.5 Precipitation

By the end of the century, global precipitation increases by 0.15–0.28 mm/day (90% range) for *Reference*, 0.13–0.24 mm/day for *ParisForever*, 0.10–0.16 mm/day for *Paris2C* and 0.08–0.13 mm/day for *Paris1.5C* (**Figure 9**). At a global scale, the uncertainty in precipitation change can be directly associated to the uncertainty in average surface-air temperature change. Lower surface-air temperatures have a direct impact on potential evapotranspiration (from the ocean and land surfaces). Thus, at a global scale, reducing near-surface warming results in smaller increases in evapotranspiration and therefore weaker support for precipitation increases. As with temperature, climate policy lowers the upper tail of the precipitation distributions more than the median.

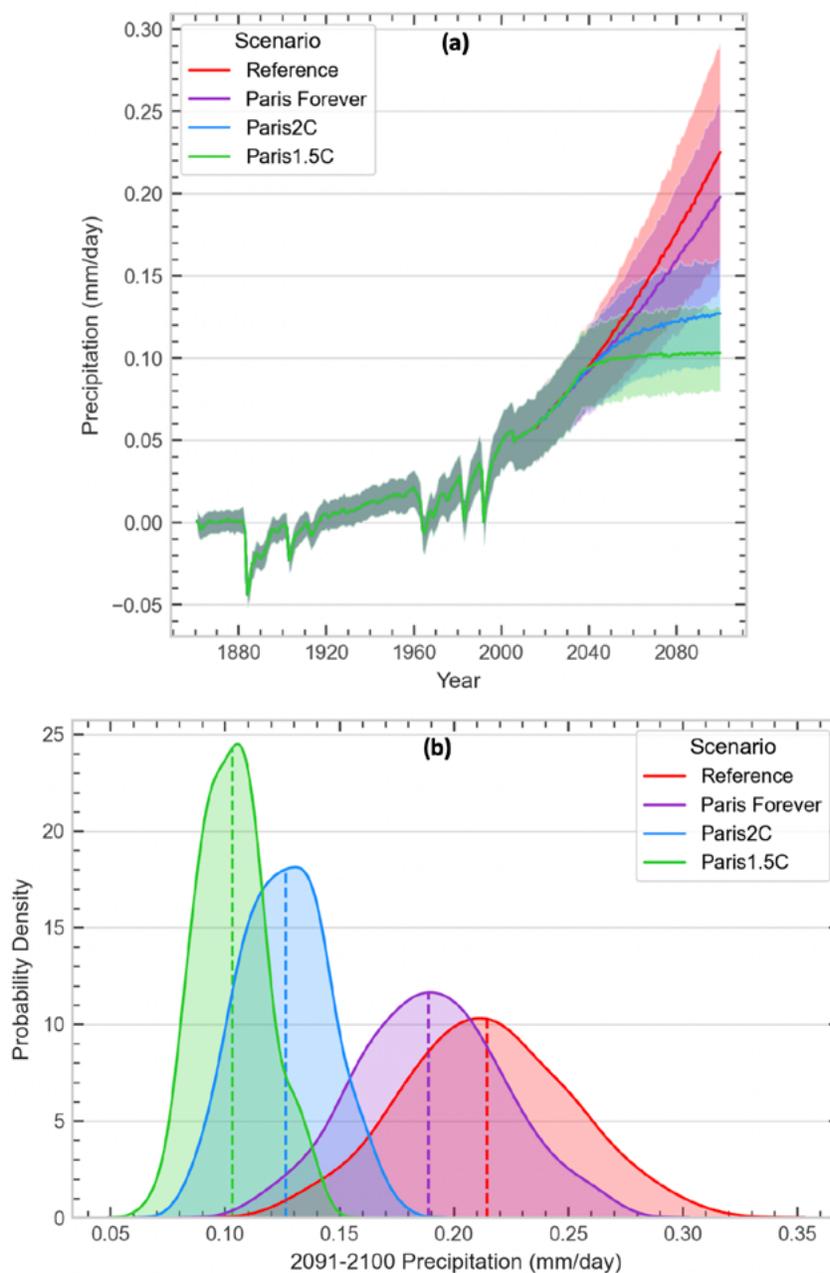
**Table 2.** Percent of ensemble runs exceeding a given temperature.

Temperature (°C)	% of Runs Exceeding Temperature			
	<i>Reference</i>	<i>Paris Forever</i>	<i>Paris2C</i>	<i>Paris 1.5C</i>
1.5	100%	100%	95%	50%
2	100%	100%	33%	<0.25%
2.5	99%	94%	<0.25%	...
3	86%	59%	...	...
3.5	50%	15%	...	...
4	14%	<0.25%	...	...
4.5	1%	...	...	...

Note: As each ensemble included 400 runs, the lowest percentage of runs resolved is 0.25% (1 out of 400). If none of the runs in the ensemble meet a criteria, we assume the percentage to be <0.25% rather than 0% as there is still a chance that the tail outcomes could extend beyond the values produced here if more than 400 ensemble members were used.



**Figure 8.** Greenhouse Gamble Wheels showing the distributions of temperature results under each ensemble scenario: (a) *Reference* (labeled on wheel as “No Paris Accord”), (b) *ParisForever* (labeled on wheel as “Paris Accord”), (c) *Paris2C* (labeled on wheel as “2°C Policy”), and (d) *Paris 1.5C* (labeled on wheel as “1.5°C Policy”).



**Figure 9.** (a) Global precipitation over time for each ensemble scenario relative to 1861–1880 (shaded areas represent 90% probability bounds. Lines are the median). (b) Frequency distributions of global precipitation in 2091–2100 relative to 1861–1880 (dashed lines are the medians).

### 3.6 Contributions to Overall Uncertainty in Climate Outcomes

The uncertainty in climate outcomes presented above for *Reference* and *ParisForever* are driven by both emissions and climate uncertainty. To explore the relative contribution of each, **Figure 10** compares the frequency distributions from the full ensembles (both emissions and climate uncertainty) to those from two different ensemble variations: (1) ensembles with median emissions from the scenarios

combined with climate uncertainty (ClimUnc, light color in the figure), and (2) ensembles with uncertain emissions combined with median climate parameter values (EmiUnc, dark color in the figure). Comparing the ClimUnc and EmiUnc ensembles, whichever is wider is a greater contributor to the overall uncertainty in the climate outcome. For CO<sub>2</sub> concentrations, uncertainty due to emissions is greater than uncertainty due to climate, especially for the *Reference* scenario (**Figure 10a**). Emissions uncertainty is

even more important for total radiative forcing (**Figure 10b**) because forcing is also affected by uncertainty in other greenhouse gases and aerosols, such as sulfate (from SO<sub>2</sub> emissions) and black carbon. However, the opposite is seen for temperature (**Figure 10c**) and precipitation (**Figure 10d**); for those outcomes, uncertainty due to climate is greater than uncertainty due to emissions. The greater effect of climate uncertainty on temperature and precipitation is not that surprising as the uncertain climate parameters most directly relate to how temperature is affected by a given level of radiative forcing, with only a secondary effect on carbon uptake by oceans and the terrestrial biosphere in response to warming.

As seen in Figure 10, using only climate uncertainty with median emissions narrows the distributions significantly for CO<sub>2</sub> concentrations and total radiative forcing, but only very slightly narrows the distributions for global temperature and precipitation. This result occurs because the addition of emissions uncertainty is largely offset by climate uncertainty. The opposite pattern emerges when there is only emissions uncertainty with median climate parameter values—the distributions are significantly narrowed for temperature and precipitation, somewhat narrowed for CO<sub>2</sub>

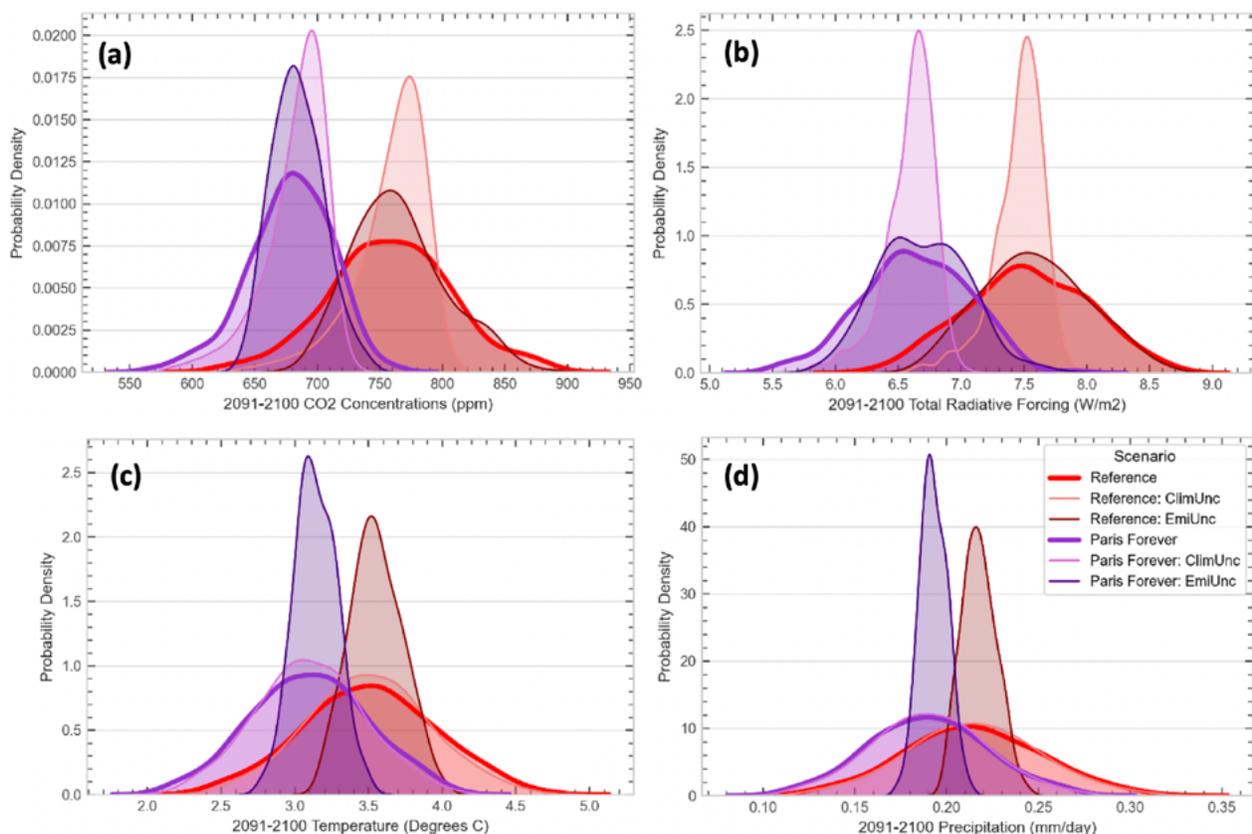
concentrations and only slightly narrowed for total radiative forcing. For total radiative forcing (and to a lesser extent CO<sub>2</sub> concentrations), the addition of climate uncertainty is largely offset by emissions uncertainty. These results indicate that cascading uncertainties are not necessarily additive, and capturing more uncertainties does not automatically mean the uncertainty range of outcomes widens because uncertainties can offset one another.

### 3.7 GDP and Welfare Effects

#### 3.7.1 Global

For all ensemble scenarios, GDP is endogenously determined in the model and therefore uncertain.<sup>2</sup> For the *Paris2C* and *Paris1.5C* scenarios, which have the same emissions trajectories for all ensemble members, the GDP impact of meeting that trajectory varies because the level of abatement needed to keep emissions on the specified trajectory, and the technology costs of doing so, varies. Here we focus on GDP results through 2050. Relative to

2 As noted previously, the particular approach used in this paper does not include climate and other environmental feedbacks on the economic system that would result from changes in the Earth system.



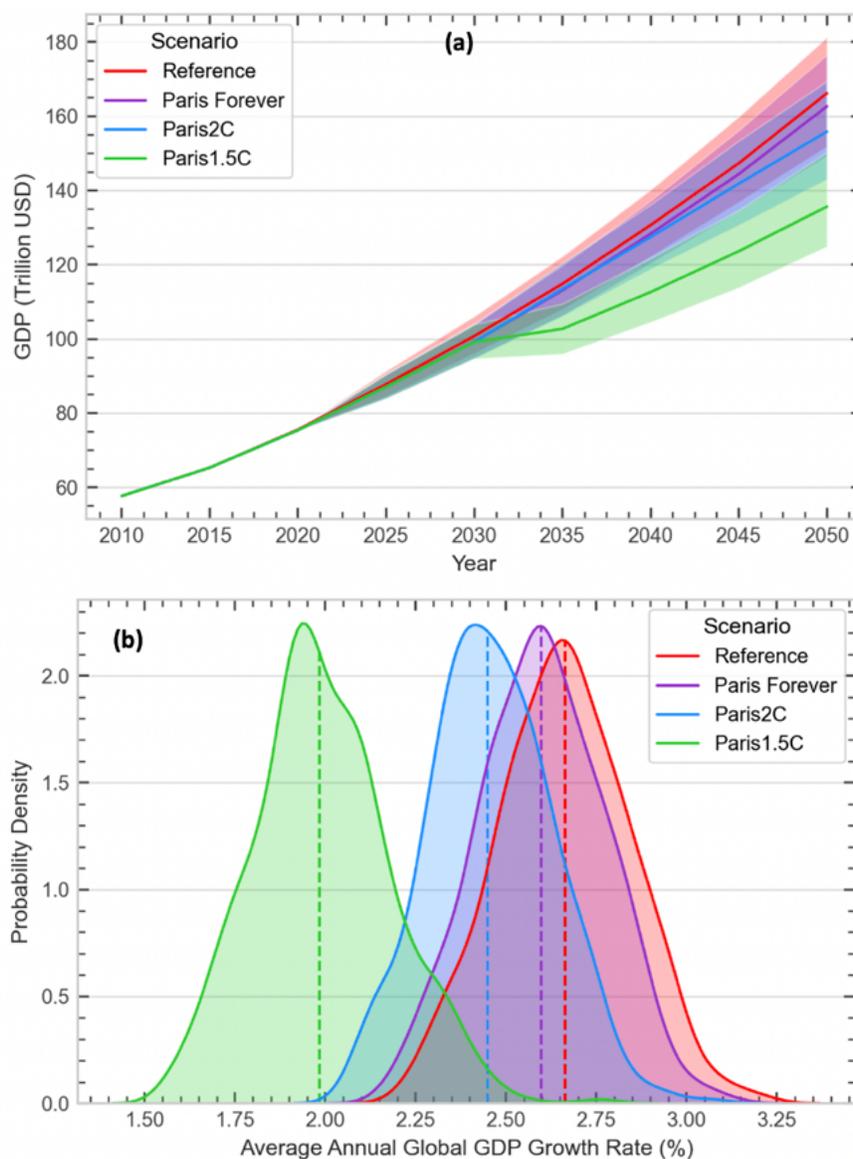
**Figure 10.** Frequency distributions for climate outcomes in 2091–2100 relative to 1861–1880 for *Reference* and *ParisForever* ensembles with emissions uncertainty plus median climate (EmiUnc, dark colors) vs. ensembles with median emissions plus climate uncertainty (ClimUnc, light colors) vs. ensembles with both emissions and climate uncertainty (medium colors). (a) CO<sub>2</sub> Concentrations, (b) Total Radiative Forcing, (c) Temperature, and (d) Precipitation.

the *Reference* scenario, median global GDP in 2050 is 2.1% lower under *ParisForever*, 6.2% lower under *Paris2C*, and 18.4% lower under *Paris1.5C* (**Figure 11a**). This shows the significant additional reduction in GDP of achieving 1.5C vs. 2C. In all scenarios, GDP is growing, with median GDP in 2050 ending up 2.2 times higher than 2020 levels under *Reference* (with a 90% range of 2–2.4x), 2.16 times higher under *ParisForever* (with a 90% range of 2–2.3x), 2.16 times higher under *Paris2C* (with a 90% range of 1.9–2.2x), and 1.8 times higher under *Paris1.5C* (with a 90% range of 1.7–2x).

In terms of the average annual GDP growth rate from 2020–2050, *Reference* has a median of 2.66%, with a 90% range of 2.36–2.96%. *ParisForever* has a median of 2.6%,

with a 90% range of 2.3–2.9%. *Paris2C* has a median of 2.45%, with a 90% range of 2.2–2.7%. *Paris1.5C* has a median of 1.97%, with a 90% range of 1.7–2.3%. As such, even stringent climate policy allows for significant global economic growth, just less than would occur in the absence of policy.

We use welfare change as a measure of policy cost. Welfare change is measured as the loss or gain in economy-wide consumption when there is mitigation policy compared to when there is not (the *Reference* scenario). Global net present value (NPV) welfare losses from 2020–2050 has a median of 1.2% under *ParisForever* (with a 90% range of 0.9–1.6%), 1.4% under *Paris2C* (with a 90% range of 1–1.9%), and 6.2% under *Paris1.5C* (with a 90% range of



**Figure 11.** (a) Global GDP 2020–2050 for each ensemble scenario (shaded areas represent 90% probability bounds. Lines are the median). (b) Frequency distributions of average annual global GDP growth from 2020–2050 (dashed lines are the medians).

5–7.7%) (**Figure 12**). This once again shows the significant additional cost of achieving 1.5C vs. 2C. A feature of the uncertainty in welfare changes is its skewness, with longer tails on the end of higher welfare losses. This results from the fact that there are many more combinations of input assumptions that can make an emissions constraint cause relatively smaller welfare losses. There are far fewer combinations that can lead to very high costs of abatement and large welfare losses, but these large negative welfare changes cannot be ruled out based on the uncertainty in input assumptions used here.

In general, there are several factors affecting these welfare changes. First, additional representation of low-carbon technologies and abatement opportunities, particularly the inclusion of negative emission technologies, would lower the cost of policy, and could truncate the tails of high welfare losses. For example, other work that includes biomass electricity with CCS (BECCS) in the MIT EPPA model shows that the availability of BECCS significantly reduces the cost of achieving stringent climate policies (Fajardy *et al*, 2020). While negative emission technologies are often not seen as playing much role until the second half of the century, their availability lowers the welfare impact in the first half of the century by providing headroom for near-term emissions, allowing for a more gradual energy transition.

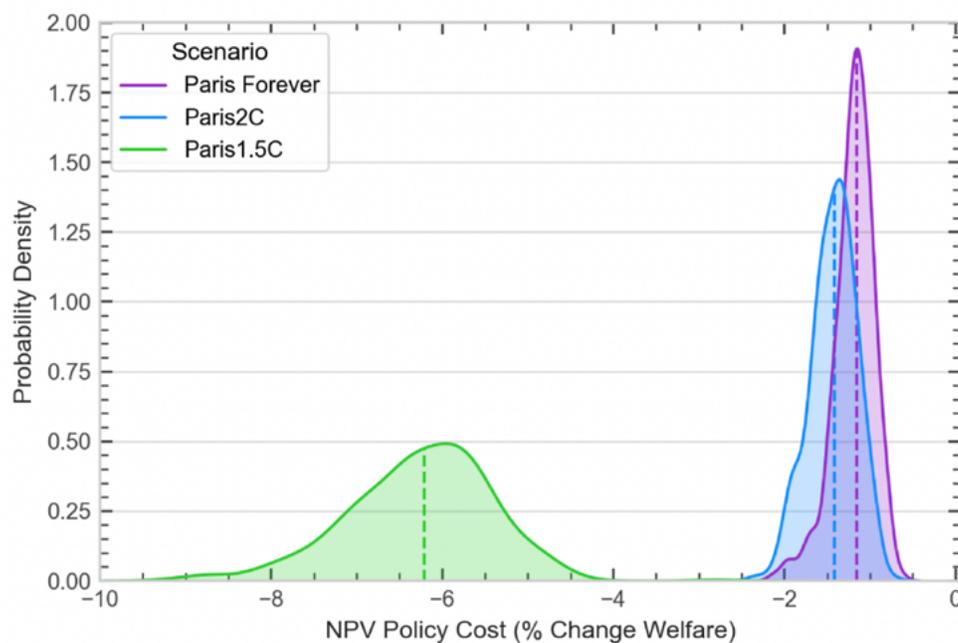
Second, the timing of the policy plays an important role in welfare changes. For example, if global carbon pricing toward achieving 1.5C with 50% probability were to begin

in 2020 rather than after 2030, we estimate a median NPV welfare losses for 2020–2050 to be 4.6% rather than 6.2%. This shows that starting the policy earlier can reduce the costs of meeting the policy, as it allows time for a more gradual transition in the early years of the policy. Similarly, if fewer emissions reductions are required in the near-term, for example because negative emissions allow for greater reductions later in the century, then the policy costs through 2050 can also be reduced.

Third, the discount rate applied in the NPV calculation is a well-known factor in determining present value estimates of welfare changes. As an example, increasing the discount rate from 4% to 5% reduces the median NPV welfare loss from 2020–2050 for *Paris1.5C* from 6.2% to 5.8%. The longer the time horizon, the greater impact of the discount rate on welfare changes.

### 3.7.2 Regional Variation

An important consideration in estimates of regional costs is the nature of the constraints imposed across regions to achieve the reductions needed in the *Paris2C* and *Paris1.5C* scenarios. Here, we determined a global carbon price trajectory, given median socio-economic parameter values, consistent with the temperature targets and designed to optimize *global* welfare. This setting results in regional emissions trajectories that ensure marginal abatement costs in each region are equal to the global carbon price. The resulting regional emissions were then used to determine the initial regional allocation of emissions allowances for the *Paris2C* and *Paris1.5C* ensembles implemented as global

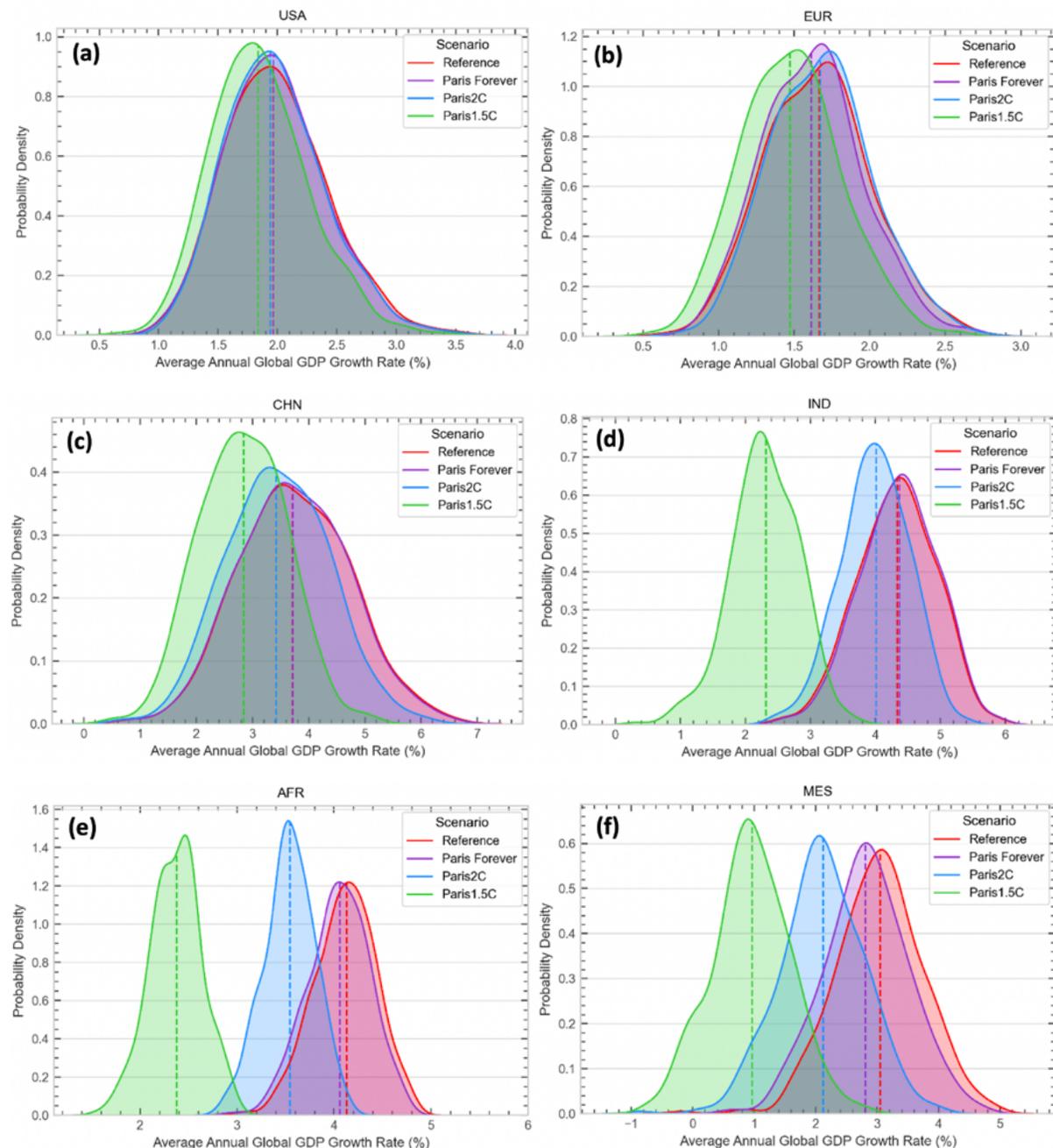


**Figure 12.** Frequency distributions of global net present value (NPV) of welfare changes (percent change in welfare relative to *Reference*) from 2020–2050, discounted at 4% (dashed lines are medians).

emissions trading systems. This implies that under the emissions cap with median parameter settings, there is no emissions trading among regions, as the marginal cost of abatement across regions is already equalized. However, uncertain economic growth, technology costs, and resource availabilities across regions will mean that within an ensemble regions will be net allowance buyers in some simulations and net sellers in others, and their net trading position may change over the time-frame of the simula-

tion. The regional cost results shown below are conditional on the regional emissions allocations obtained by global optimization under median climate parameters. Different regional allocations would have different regional cost implications, and are a worthy topic for future research.

There is significant variation in GDP growth across regions under the scenarios. **Figure 13** shows the frequency distribution of the average annual GDP growth rate from 2020–2050 for six selected regions: the United States (USA),



**Figure 13.** Average annual GDP growth rate from 2020–2050 for each ensemble scenario for selected regions: (a) United States (USA), (b) Europe (EUR), (c) China (CHN), (d) India (IND), (e) Africa (AFR) and (f) Middle East (MES) (dashed lines are medians).

Europe (EUR), China (CHN), India (IND), Africa (AFR) and the Middle East (MES). The median and 90% bounds are given in **Table 3**. For the USA and Europe, the ensemble scenarios are largely on top of one another. Median average annual GDP growth in the USA is just below 2% for all scenarios except *Paris1.5C*, which is 1.84%. For Europe, the GDP impact of *Paris1.5C* is a bit greater than in the USA, but still relatively small. Europe even has the potential for GDP gains under *Paris2C* as a seller of emissions permits. There is less overlap of ensemble scenarios for China, and even less for India, Africa and the Middle East.

Under stringent policy, the world must shift away from oil (as shown in the next section). Since oil is such a central part of the economy in the Middle East, that global energy transition has a significant cost in the Middle East. Under *Paris1.5C* the Middle East actually becomes a permit seller.

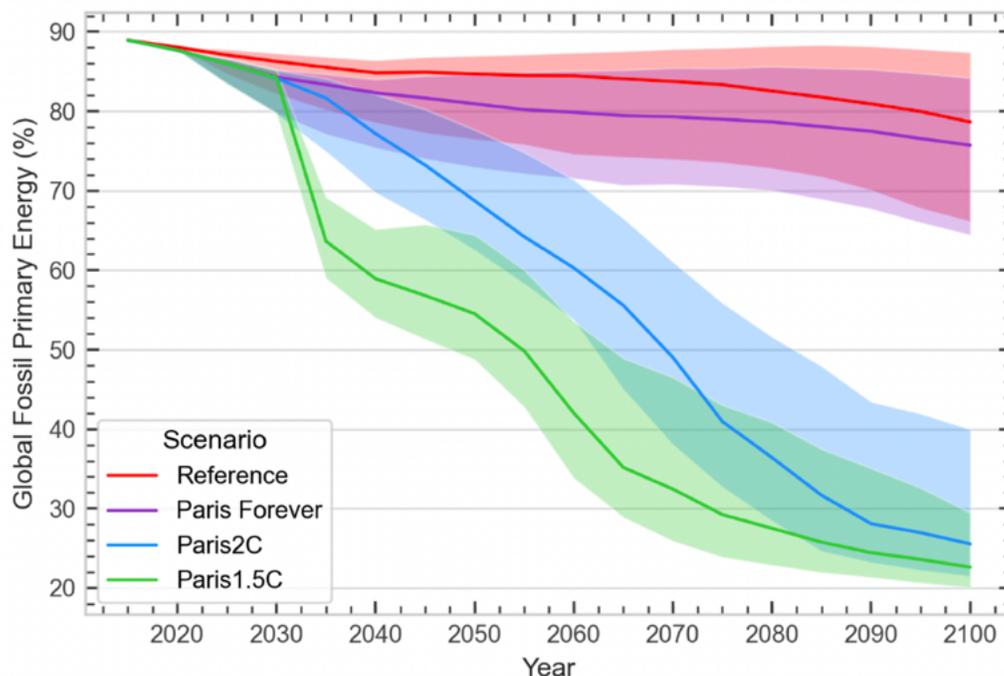
Because its economy has dropped so much due to the global transition away from oil, emissions in the region fall below the cap, allowing for the sale of permits.

These results raise serious issues of equity among countries, especially between wealthier countries where the economies are now less energy-intensive, and poorer countries still in a relatively energy-intensive stage of growth. If a global trading system were to develop as the leading approach for reducing emissions, allowance allocation can be one mechanism to facilitate financial transfers from developed to developing countries. However, with uncertainty in growth and other factors, determining an allowance allocation that would achieve a given level of transfer would be a challenge.

These results also highlight potential areas for future model development. The Middle East shows very large welfare

**Table 3.** Average annual GDP growth rate 2020–2050 in selected regions.

Average Annual GDP Growth Rate 2020–2050: Median (90% range)				
	<i>Reference</i>	<i>ParisForever</i>	<i>Paris2C</i>	<i>Paris1.5C</i>
<b>USA</b>	1.97 (1.37–2.76)	1.96 (1.36–2.72)	1.95 (1.39–72)	1.84 (1.27–2.58)
<b>Europe</b>	1.67 (1.10–2.25)	1.63 (1.09–2.18)	1.69 (1.15–2.26)	1.49 (0.97–2.04)
<b>China</b>	3.70 (2.27–5.43)	3.69 (2.24–5.41)	3.43 (2.03–4.94)	2.81 (1.68–4.07)
<b>India</b>	4.36 (3.35–5.24)	4.39 (3.41–5.27)	4.00 (3.14–4.81)	2.29 (1.43–3.12)
<b>Africa</b>	4.13 (3.58–4.61)	4.06 (3.51–4.54)	3.55 (3.11–3.95)	2.39 (1.91–2.81)
<b>Middle East</b>	3.05 (1.90–4.17)	2.83 (1.70–3.96)	2.10 (0.93–3.17)	0.95 (-0.12–1.96)



**Figure 14.** Global fossil primary energy share over time for each ensemble scenario (Shaded areas represent 90% probability bounds. Lines are the median).

costs because it is a fossil fuel exporter in a world that where there is very little demand for fossil fuels. The constant elasticity of substitution (CES) nature of the CGE model prevents large sectoral changes in the underlying structure of an economy, and so as the global oil market collapses, the economy in the Middle East is hit hard. Understanding and modeling how the structure of the economy could shift to other industries is important in determining whether such oil-dependent economies can avoid large economic impacts.

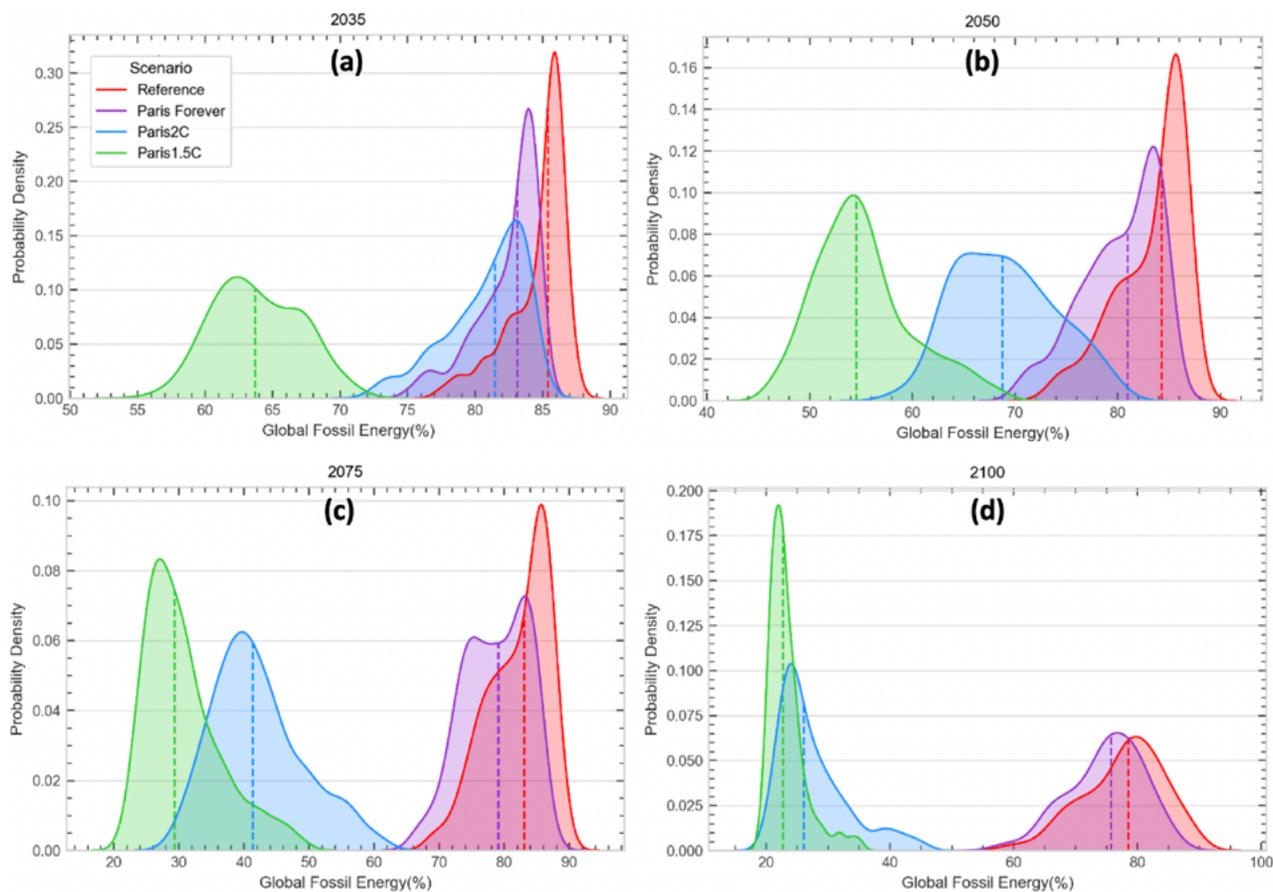
### 3.8 Energy

An energy transition away from fossil fuels is required in order to achieve the long-term temperature goals of the Paris Agreement. This can be achieved by both switching to low-carbon energy sources and by reducing the amount of energy used in both production and consumption (which is driven by the ease of substituting energy for non-energy inputs to production and consumption). **Figure 14** shows global fossil primary energy (including energy deployed with CCS) as a percentage of total global primary energy use over time. In 2020, the fossil share is 88%, and while it does fall in all scenarios, the share in 2100 is dramatically different in *Reference* and *ParisForever* compared with

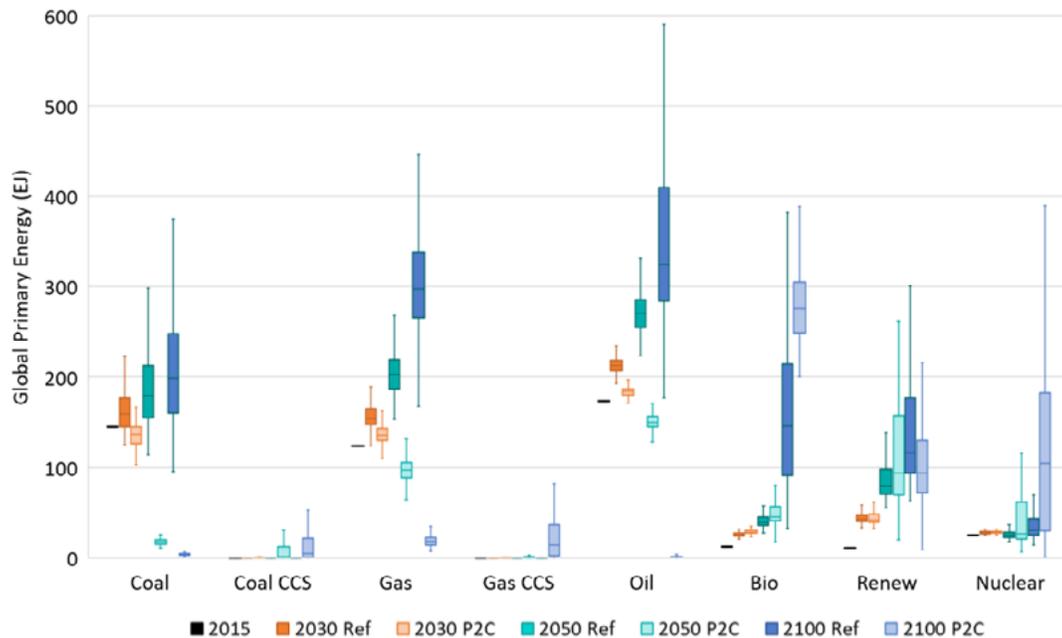
*Paris2C* and *Paris1.5C* scenarios. The median 2100 fossil share is 79% (with a 90% range of 66–87%) under *Reference*, 76% (with a 90% range of 64–84%) under *ParisForever*, 26% (with a 90% range of 21–46%) under *Paris2C*, and 23% (with a 90% range of 20–29%) under *Paris1.5C*.

**Figure 15** shows frequency distributions of the fossil energy share for various points in time: 2035, 2050, 2075 and 2100. The fossil share drops early on under *Paris1.5C*, falling to median of about 65% in 2035. By 2050, the median fossil share declines to about 70% under *Paris2C* and 55% under *Paris1.5C*. By 2075, the median fossil share falls to about 40% under *Paris2C* and 30% under *Paris1.5C*, ultimately ending up at 26% and 23%, respectively, in 2100.

As fossil energy is phased down under stringent climate policy, other low-carbon energy sources take its place. **Figure 16** shows the uncertainty in global primary energy by source for 2030, 2050 and 2100 under the *Reference* and *Paris2C* scenarios. The sources of primary energy in our model are coal (with or without CCS), natural gas (with or without CCS), oil, bioenergy, renewables (wind and solar), nuclear and hydro (hydro is not shown in Figure 17 as it is modeled as a fixed resource so there is virtually no un-



**Figure 15.** Frequency distributions of the global fossil primary energy share for: (a) 2035, (b) 2050, (c) 2075 and (d) 2100 (dashed lines are medians).



**Figure 16.** Boxplots of global primary energy by source in 2030, 2050 and 2100 under *Reference* and *Paris2C*. The 2015 emissions are shown in black as a point of reference.

certainty around its deployment). The amount of primary energy from each of these sources is uncertain. Notably, *Reference* (darker shades in the figure) and *Paris2C* (lighter shades in the figure) diverge significantly for coal, gas and oil— under *Reference* all three fossil energy sources grow over time, whereas under *Paris2C* they decline over time (starting in 2025 for coal, 2045 for gas and 2050 for oil). Under *Paris2C*, there is a particularly dramatic reduction in primary energy from coal between 2030 and 2050, and from oil between 2050 and 2100. The oil use is offset by a dramatic increase in bioenergy between 2050 and 2100, largely in the form of bio-oil as a substitute for refined oil. However, even under *Reference* there is a large expansion of bioenergy by 2100. Coal and gas with CCS are unused under *Reference* as there is not an economic case for them. There is some potential for coal and gas CCS under *Paris2C* in the second half of the century.

In terms of making energy investment decisions today in the face of policy uncertainty, the results suggest that renewables offer the safest bet, with great future potential regardless of the level of policy. They end up somewhat lower in 2100 in *Paris2C* than in *Reference* because overall consumption, including electricity consumption, is lower under stringent policy. However, if the model represented more options for electrification, it is possible that total electricity consumption would increase in the *Paris2C* scenario relative to the *Reference* scenario, and renewables would grow beyond *Reference* levels throughout the century. Electrification opportunities is an area for further model development. Advanced nuclear generation also has the

potential to play an important role under *Paris2C* in the second half of the century. The large uncertainty range for nuclear is largely driven by China, where nuclear has the potential to play a large role in the country's energy mix.

#### 4. Conclusions

Uncertainty is unavoidable in economic, energy and climate projections. However, as understanding of underlying technology and economic factors and Earth system responses advances, updated estimates of uncertainty will be needed to help inform mitigation and adaptation decisions. This paper presents a consistent framework for uncertainty quantification in coupled human-Earth system models, which supports a broad exploration of global-change uncertainty and provides a probabilistic interpretation of socio-economic and climate outcomes. The analysis results enable a risk management approach to decisions in response to global climate changes.

The Paris Agreement set a goal of limiting global average surface temperature warming to “well below” 2°C, and to attempt a 1.5°C target. These temperature targets are often translated into radiative forcing, concentrations, or emissions targets or budgets. Typically, the relationship between emissions, concentrations, radiative forcing and temperature is expressed without uncertainty. Here we account for uncertainty in that relationship, exploring the degree to which a given emissions trajectory can be expected to meet a proposed climate target. The application

illustrates that emissions targets will need to be adjusted over time as uncertainty in the climate system is resolved.

Our results show how climate policy lowers the upper tail of the temperature change more than the median, and that even relatively modest policies can significantly reduce the likelihood of high temperature outcomes. We also illustrate the fact that representing more input uncertainties does not automatically widen the range of outcomes because uncertainties can offset one another. We find that, even under a stringent climate policy designed to meet 1.5°C, the global economy continues to grow significantly, but that burden sharing issues remain as policy costs can vary significantly across regions. In terms of the energy future, renewable sources are expected to expand significantly regardless of the level of future policy.

This study advances and updates an earlier analysis conducted using the MIT IGSM. The simulations' results show lower, though still significant, surface warming in the *Reference* scenario than previously, with median end-of-century warming of 3.5°C and a 90% range of 2.8–4.3°C. This compares with a median of 5.7°C in the earlier study. About 0.5°C of the difference is due to updated estimates in the human system and the rest of the difference is explained by changes in Earth system estimates. This uncertainty quantification approach can also guide future research and model development efforts. It can identify key components and assumptions in models and uncertainties of greatest importance or least understanding, highlighting areas that warrant the most attention. For example, this

effort brought to light several areas for further research and model development, including the representation of additional abatement options (e.g. for agriculture, industry and residential sectors, and elaboration of electrification pathways), the representation of structural economic shifts in CGE models, outcomes at subglobal levels (regions, sectors, technologies), and implications of regional emissions allocations.

This approach to uncertainty quantification can also guide scenario development. Whereas standardized scenarios constrain the uncertainty space explored, this probabilistic ensemble approach can give a more comprehensive view of uncertainty, and scenarios (and sensitivity tests) can be developed that connect to the distributions of inputs and/or outputs. The ensemble results can also be utilized in scenario discovery techniques to identify conditions consistent with outcomes of interest, for example salient tipping points, large socio-environmental inequities or particular energy or economic outcomes.

Another contribution of our approach is the insight provided into how multiple uncertainties interact and the relative human vs. Earth system contributions to uncertainty in climate-related outcomes.

### Acknowledgements

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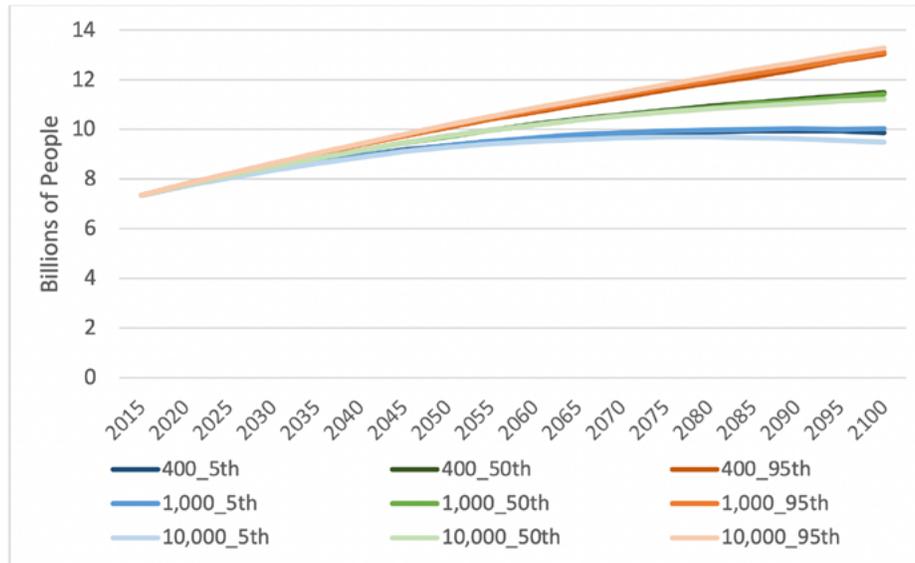
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## Appendix A. Input Probability Distributions

The development of probability distributions for socioeconomic parameters is described in Morris *et al.*, (2021) and for Earth system parameters in Libardoni *et al.*, (2019, 2018a,b). This appendix summarizes the probability distributions for all uncertain parameters.



**Figure A.1.** World population for the 5<sup>th</sup>, 50<sup>th</sup> and 95<sup>th</sup> percentiles based on 400 samples, 1,000 samples and 10,000 samples from the UN (Morris *et al.*, 2021).

**Table A.1.** Mean and standard deviation of historical annual growth rates, and 5<sup>th</sup>, 50<sup>th</sup> and 95<sup>th</sup> percentiles of projected average annual growth rates for 2015–2100 (Morris *et al.*, 2021).

Region	Historical 1950–2015		Projected Average Annual Growth Rate 2015–2100		
	Av Annual	Std Dev	5 <sup>th</sup>	50 <sup>th</sup>	95 <sup>th</sup>
AFR	3.9%	1.7%	3.1%	3.4%	3.7%
ANZ	3.5%	1.7%	1.7%	2.1%	2.5%
ASI	5.8%	2.5%	1.8%	2.3%	2.8%
BRA	4.4%	3.7%	2.1%	3.0%	3.8%
CAN	3.5%	2.4%	1.3%	1.8%	2.3%
CHN	6.9%	5.1%	2.0%	2.9%	3.9%
EUR	2.9%	2.0%	1.1%	1.5%	1.9%
KOR	6.8%	5.1%	1.4%	2.3%	3.3%
IDZ	4.9%	4.2%	1.8%	2.7%	3.5%
IND	5.0%	3.1%	2.7%	3.4%	4.0%
JPN	4.5%	4.2%	0.7%	1.5%	2.2%
LAM	3.4%	2.7%	2.3%	2.7%	3.3%
MES	4.9%	4.0%	2.0%	2.7%	3.3%
MEX	4.2%	3.5%	2.1%	2.7%	3.4%
REA	4.6%	1.9%	3.0%	3.4%	3.7%
ROE	2.7%	5.3%	1.6%	2.6%	3.7%
RUS	2.7%	6.0%	0.9%	1.9%	3.0%
USA	3.1%	2.3%	1.3%	1.7%	2.2%
WORLD	3.9%	1.4%	2.1%	2.3%	2.5%

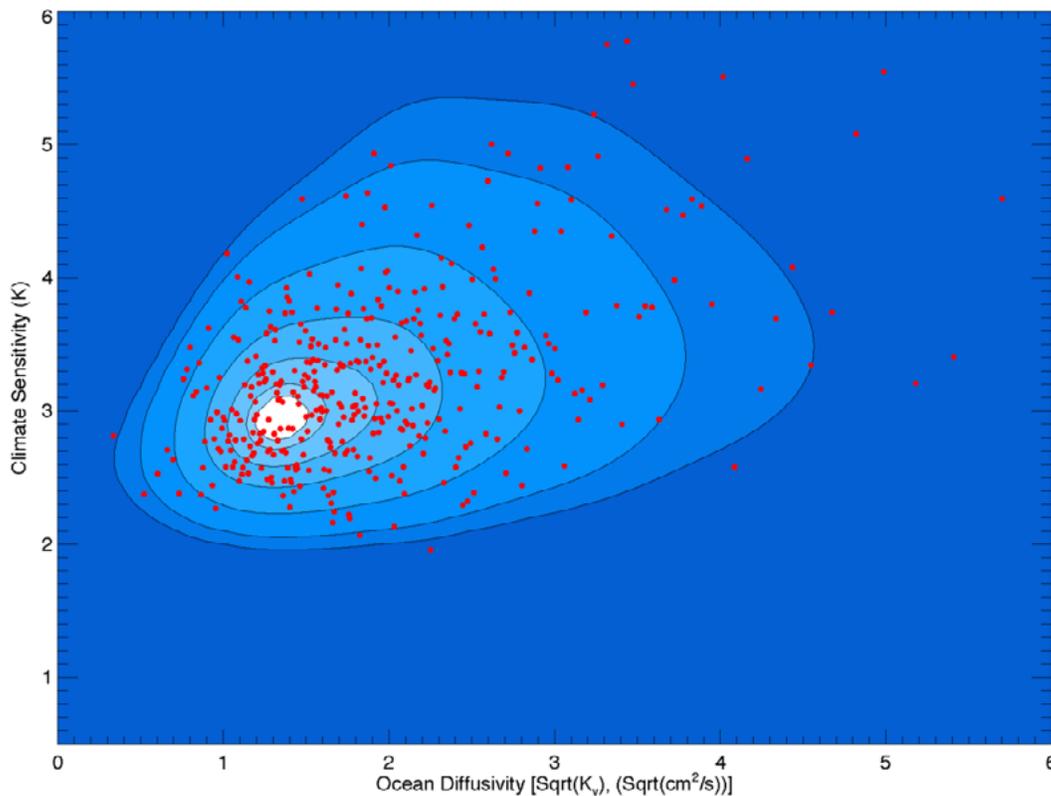
**Table A.2.** Distributions for Uncertain Socio-Economic Model Parameters (Morris *et al.*, 2021).

Parameter Category	Parameter	Specific Region/Sector	Distribution
Population		By Region	See Figure A.1
GDP (Capital and Labor Productivity)		By Region	See Table A.2
AEEI		Each region with separate distribution	Normal(1,0.55)
Advanced Technology Costs (Uniform distributions of cost scalars with 50% probability between minimum and median, and 50% between median and maximum. Median = 1. [MIN, MAX] is given here for each technology.)		NGCC	[0.798, 1.148]
		New Coal	[0.643, 1.410]
		Nuclear	[0.590, 1.558]
		Solar	[0.542, 2.083]
		Wind	[0.489, 2.035]
		Bioelec	[0.504, 1.659]
		Gas CCS	[0.816, 1.335]
		Coal CCS	[0.840, 1.536]
		BioCCS	[0.553, 1.767]
		WindGas	[0.544, 1.767]
	WindBio	[0.378, 2.282]	
	Bio-Oil	Pearson5(14.8, 40.6, Shift(1))	
Fossil Fuel Resource Stocks		Oil	Beta(1.537,3.5787,0.3405,2.7563)
		Gas, Coal	Beta(1.1127,2.213,0.2552,7501)
Technology Penetration Rates		All advanced technologies	Uniform(1.014, 1.589)
Urban Pollutant Initial Inventories	SO <sub>2</sub>	Each region with separate distribution	Normal(1,0.3)
	CO	ALL	Normal(1, 0.25)
	BC, OC, VOC, NO <sub>x</sub> , NH <sub>3</sub>	ALL	Lognormal(1.0439, 0.3132)
	CH <sub>4</sub>	AGRI	Beta(1.8, 1.8, 0.4, 1.6)
		COAL, OTHR, FOOD	Beta(2, 2, 0.89, 1.11)
		GAS, OIL, EINT	Beta(2, 2, 0.86, 1.14)
		FD	Beta(1.8, 1.8, 0.96, 1.04)
ROIL	Beta(2, 2, 0.86, 1.14)		
Urban Emission Trends		SO <sub>2</sub> , BC, OC	Beta(7, 7, 0.155, 3.107)
		NO <sub>x</sub> , VOC, CO, NH <sub>3</sub>	Beta(3, 7, 0.4114, 2.467)
Elasticities of Substitution	Energy vs. Capital/Labor	ALL	Normal(1, 0.3)
	Electric vs. Non-Electric	ALL	Normal(1, 0.15)
	Interfuel Substitution	Electricity, Energy Int.	Normal(1, 0.25)
		All Others	Normal(1, 0.15)
	Labor vs. Capital	Agriculture	Gamma(1.2564, 1.0666)
		Oil, Coal, Natural Gas	Normal(1, 0.087229)
		Electricity	Gamma(1.2564, 1.0666)
		Energy Intensive	Normal(1, 0.2158)
		Services	Gamma(25.82, 0.03923)
		Other	Beta(4.9776, 5.1354, 0, 2.0338)
		Transportation	Gamma(42.252, 0.02119)
		Dwellings	Beta(4.9776, 5.1354, 0, 2.0338)
		Food	Beta(4.9776, 5.1354, 0, 2.0338)
	Energy vs. Non-Energy	Final Demand	Loglogistic(0, 1, 3.9743)
	Resource Supply	Coal, Oil, Natural Gas	Beta(1.5, 2.8, 0.507, 2.03)

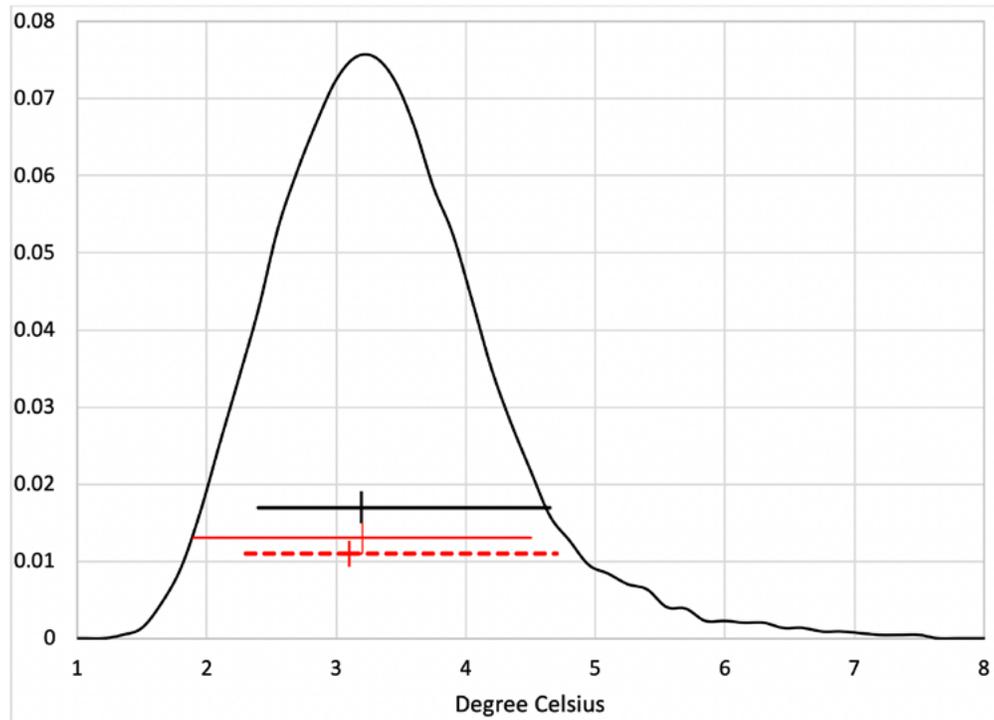
**Table A.2** (continued). Distributions for Uncertain Socio-Economic Model Parameters.

Parameter Category	Parameter	Specific Region/Sector	Distribution
Abatement Cost Elasticities	CH <sub>4</sub> Elas. In Agriculture	USA, CAN	Pearson5(4.8285, 4.044)
		MEX, IDZ, BRA, AFR, LAM	Beta(3.2254, 3.1, 0, 1.957)
		JPN	Beta(3.207, 4.709, 0.143, 2.303)
		ANZ	Beta(7.8, 7.8, 0, 2.0)
		EUR	Beta(2.8, 5.6, 0.042, 2.23)
		ROE	Beta(5.6, 6.8, 0.024, 0.193)
		RUS	Beta(3.7, 5.6, 0, 2.56)
		ASI, KOR	Beta(2.1, 4.1, 0, 3.121)
		CHN	Loglogistic(-0.053, 1.053, 3.657)
		IND	Beta(7.57, 11.355, 0.0017, 2.53)
		MES	Beta(3.2284, 3.46, 0, 2.079)
		REA	Beta(3.229, 3.4608, 0, 2.0795)
	N <sub>2</sub> O Elas. in Agriculture	USA, CAN, JPN, EUR, ANZ, KOR	Beta(8.7, 7.8, 0, 1.89)
		MEX, ROE, RUS, ASI, CHN, IND, BRA, AFR, MES, LAM, REA, IDZ	Beta(5.094, 5.294, 0, 2.042)
		RUS	Beta(7.795, 5.5, 0.2532, 1.517)
ROE		Beta(4.2, 4.3, 0, 2.026)	
Vintaging	ALL	Gamma(10.428, 0.09904)	

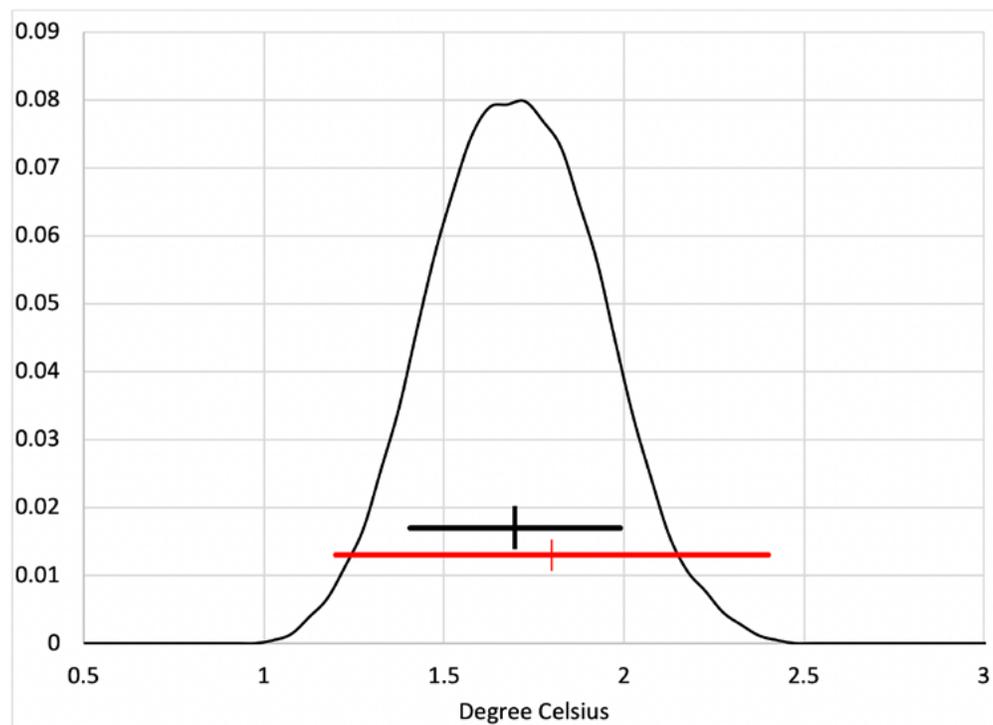
Note: All distributions are normalized to have a median of 1.



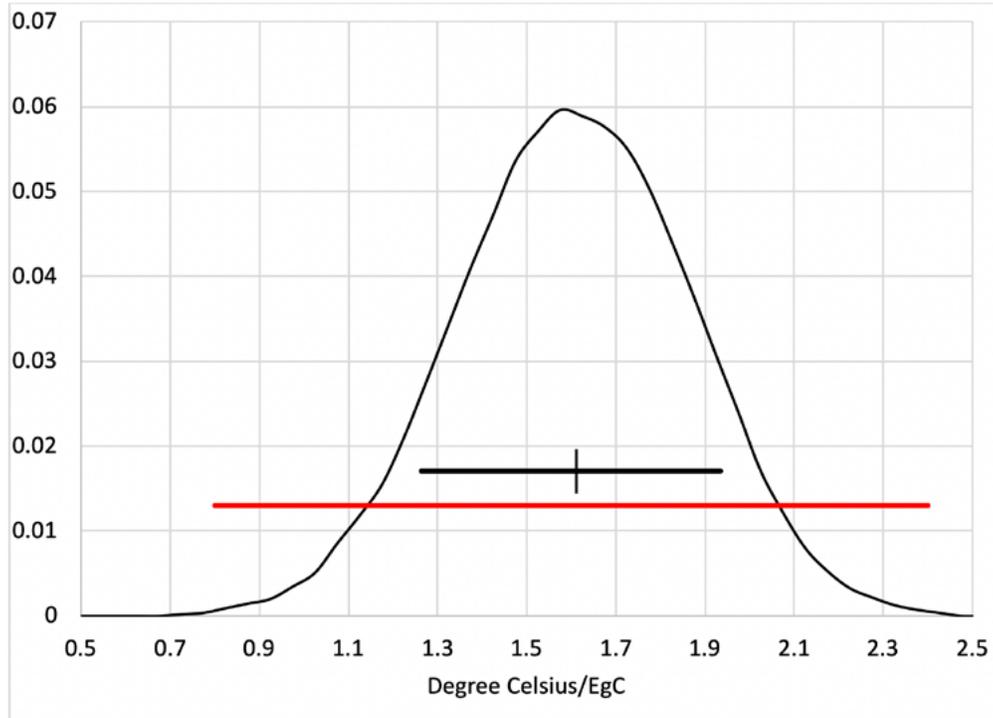
**Figure A.2.** Distribution of climate sensitivity (CS) and the rate of ocean heat uptake (square root of vertical diffusion coefficient, Kv). Red dots show values of CS and SQRT(Kv) for 400 samples. The contour lines are for the 5, 10, 25, 50, 75, 90 and 95% percentiles (Sokolov *et al.*, 2018).



**Figure A.3.** Frequency distribution of climate sensitivity (CS). Black vertical line shows the median value and the black horizontal bar shows the 90% probability interval (Sokolov *et al.*, 2018). Red solid lines are the CMIP5 estimate from Table 9.5 of IPCC (2013). Red dashed lines are estimates from Sherwood *et al.*, (2020).

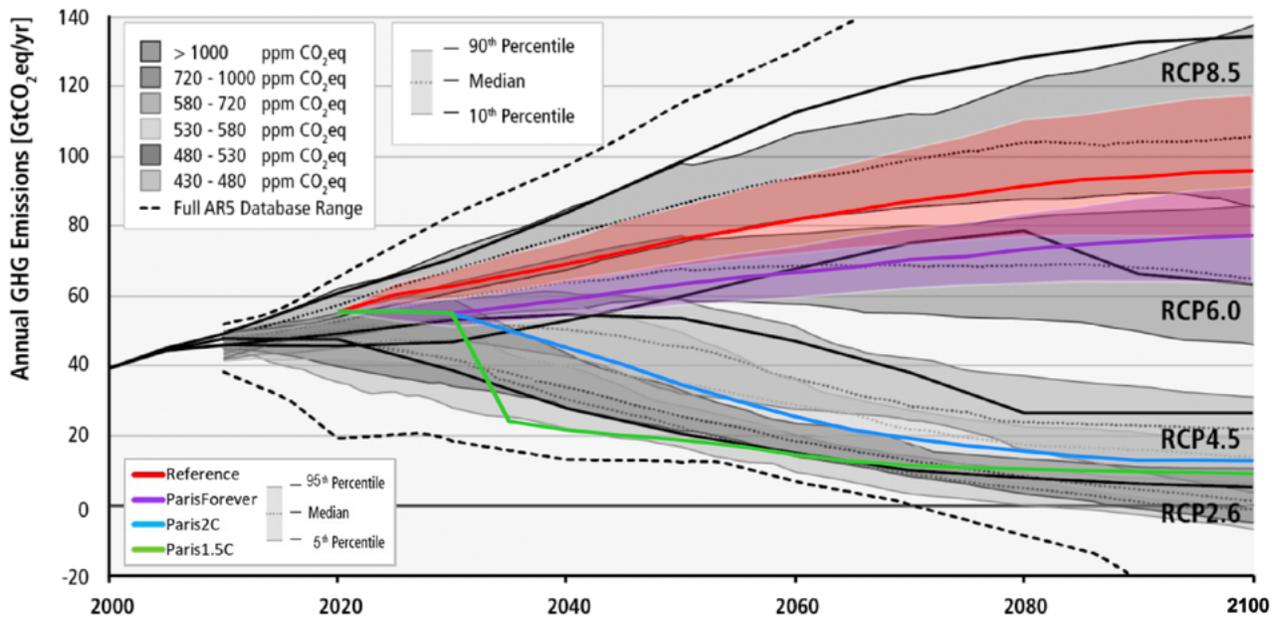


**Figure A.4.** Frequency distribution of transient climate response (TCR). Black vertical line shows the median value and the black horizontal bar shows the 90% probability interval (Sokolov *et al.*, 2018). Red lines are the CMIP5 estimate from Table 9.5 of IPCC (2013).



**Figure A.5.** Frequency distribution of transient climate response to emissions (TCRE). Black vertical line shows median value and the black horizontal bar shows the 90% probability interval (Sokolov *et al.*, 2018). Red line shows the CMIP5 estimate from Gillett *et al.*, (2013). (EgC is exagrams of carbon).

### Appendix B. Comparing Emission Results to Emissions from IPCC AR5 Report

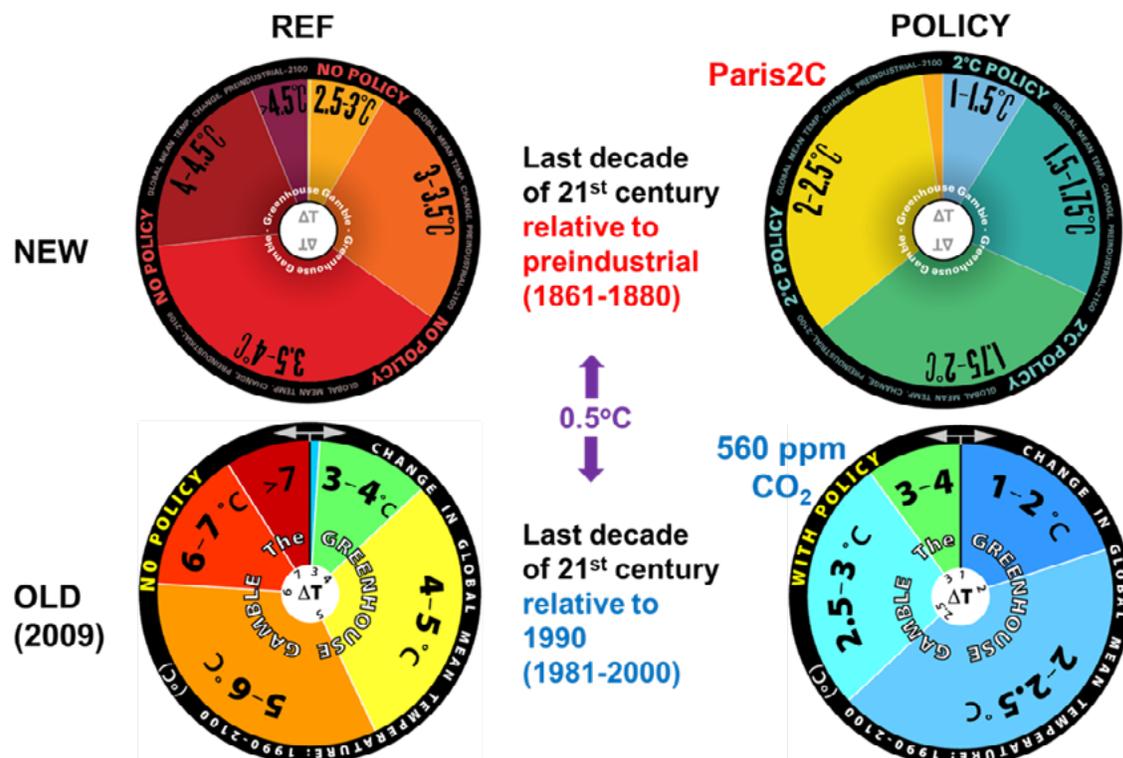


**Figure B.1.** Total global GHG emissions range (for the *Reference* and *ParisForever* ensembles) and emissions constraint (for the *Paris2C* and *Paris 1.5C* ensembles) in Gt CO<sub>2</sub>eq compared with scenarios in the IPCC AR5 Report. (Source for AR5 figure: IPCC (2014)).

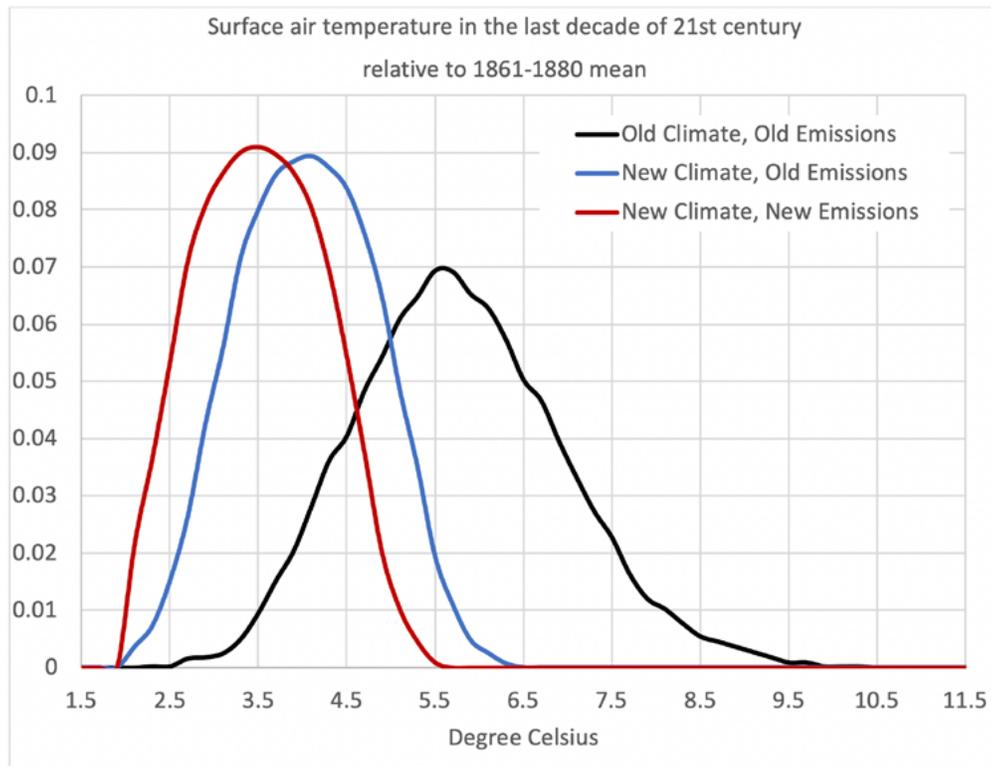
## Appendix C. New vs. Previous Wheels

The results in this study differ from those in the previous study (Sokolov *et al.*, 2009 and Webster *et al.*, 2012) for several reasons. The key differences in this study compared to the previous study include:

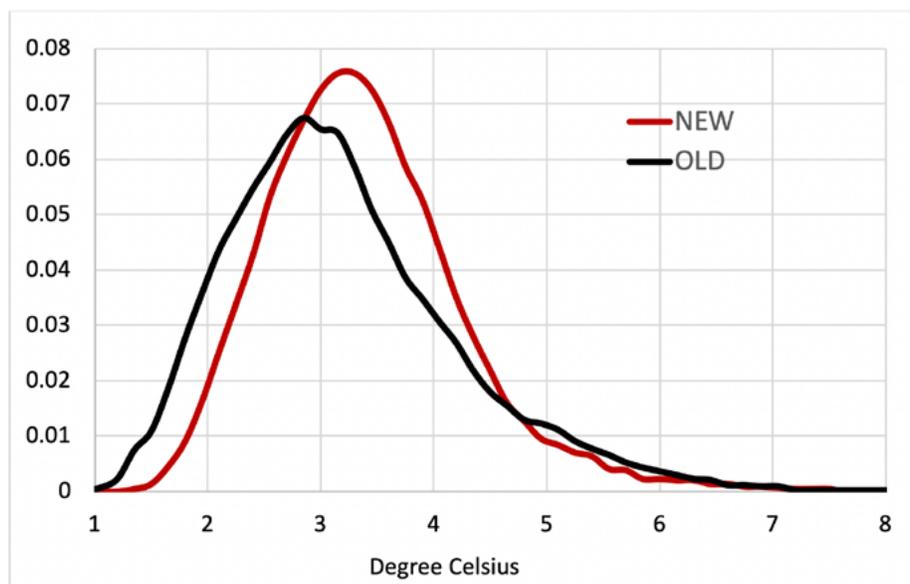
- New version of MIT Earth System Model (MESM) (see Sokolov *et al.*, 2018)
  - ◆ Updates to forcings: CH<sub>4</sub>, N<sub>2</sub>O, aerosols
  - ◆ Updates to land system's hydrology and biogeophysics
- New version of EPPA model (see Chen *et al.*, 2016; Morris *et al.*, 2019)
  - ◆ Updates to GDP growth rates (lower, especially for China), population, technology costs (e.g. cheaper renewables), and other assumptions
  - ◆ Updates to “Reference” scenario: now includes projected expansion of renewables due to mandates, etc.
  - ◆ Benchmarked model to recent history, which implicitly captures a array of policies that result in lower emissions
  - ◆ Lower “business-as-usual” emissions result from these changes
- New climate parameter distributions (see Libardoni *et al.*, 2019, 2018a,b)
- New socio-economic parameter distributions (see Morris *et al.*, 2021)
- Different policy scenarios (e.g. *Paris2C* scenario vs. 560 ppm CO<sub>2</sub> scenario)



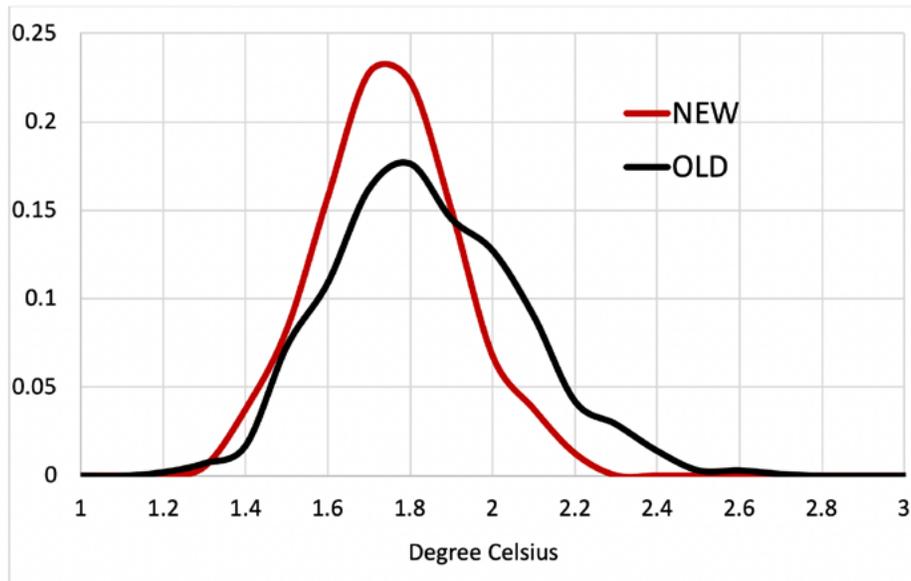
**Figure C.1.** Comparison of Greenhouse Gamble Wheels from this study for the *Reference* and *Paris2C* scenarios (top row) to those from the previous study for the *No Policy* and *Level 2* scenarios (bottom row). The new *Paris2C* scenario was specifically designed to achieve 2°C with a 66% probability, and has a median end-of-century temperature change of 1.9°C, relative to 1861–1880. The *Level 2* scenario in the previous study has median end-of-century concentrations of 560 ppm CO<sub>2</sub> (660 ppm CO<sub>2</sub>eq), which resulted in a median end-of-century temperature change of 2.3°C, relative to 1981–2000. It is important to note that results in the previous study were reported relative to the 1981–2000 average, whereas this new study reports results relative the 1861–1880 average. The difference between the 1981–2000 average and the 1861–1880 average is 0.5°C.



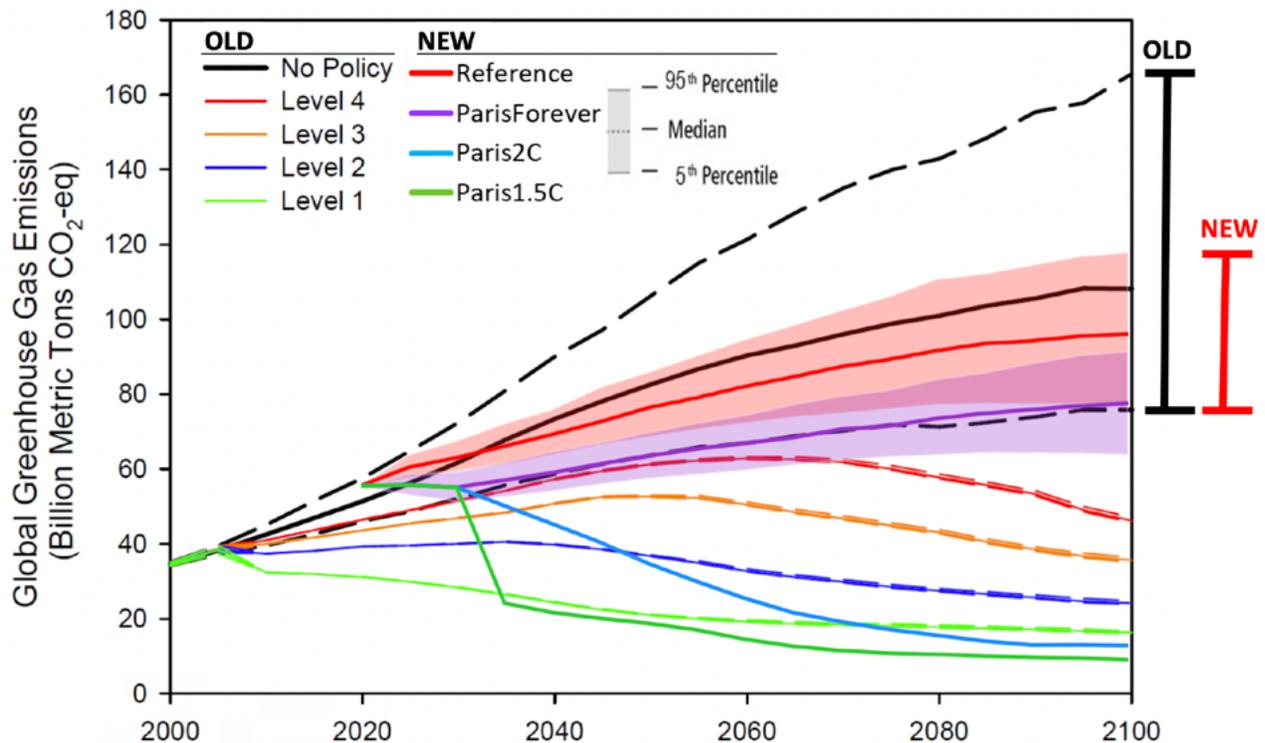
**Figure C.2.** Comparison of distributions of global warming under the reference scenario from: (1) this study—New Climate, New Emissions (in red), which has a median of 3.5°C, (2) the previous study—Old Climate, Old Emissions (in black), which has a median of 5.7°C, and (3) ensemble simulations using the latest Earth system model and climate distributions from this study but emissions from the previous study—New Climate, Old Emissions (in blue), which has a median of 4.0°C. This indicates that of the difference in reference median surface warming results between this study (3.5°C) and the previous study (5.7°C), 0.5°C can be explained by the difference in anthropogenic emissions, and the remaining difference is due to differences in the climate system response to emissions.



**Figure C.3.** Frequency distribution of climate sensitivity (CS) from this study (NEW, in red) compared to previous study (OLD, in black).



**Figure C.4.** Frequency distribution of transient climate response (TCR) from this study (NEW, in red) compared to previous study (OLD, in black).



**Figure C.5.** Comparison of global greenhouse gas emissions results from this study to those from the previous study. From this study, the 90% range of global GHG emissions are shown as shaded bands for *Reference* (red) and *ParisForever* (purple) ensembles (with the median shown as a solid line), and the global GHG emissions constraint is shown for the *Paris2C* (blue) and *Paris1.5C* (green) ensembles. These are overlaid onto the results from the previous study (see Webster *et al.*, 2012), for which solid lines indicate median emissions, and dashed lines indicate 5% and 95% bounds on emissions. In the previous study, the policy scenarios are No Policy (black), Level 4 (red, 710 ppm CO<sub>2</sub>), Level 3 (orange, 640 ppm CO<sub>2</sub>), Level 2 (blue, 560 ppm CO<sub>2</sub>), and Level 1 (green, 480 ppm CO<sub>2</sub>).

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