

# Quantifying both socioeconomic and climate uncertainty in coupled human–Earth systems analysis

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Information about the likelihood of various outcomes is needed to inform discussions about climate mitigation and adaptation. Here we provide integrated, probabilistic socio-economic and climate projections, using estimates of probability distributions for key parameters in both human and Earth system components of a coupled model. We find that policy lowers the upper tail of temperature change more than the median. We also find that while human system uncertainties dominate uncertainty of radiative forcing, Earth system uncertainties contribute more than twice as much to temperature uncertainty in scenarios without fixed emissions paths, reflecting the uncertainty of translating radiative forcing into temperature. The combination of human and Earth system uncertainty is less than additive, illustrating the value of integrated modeling. Further, we find that policy costs are more uncertain in low- and middle-income economies, and that renewables are robust investments across a wide range of policies and socio-economic uncertainties.

Addressing climate change is ultimately a challenge of risk management, recognizing that our ability to predict future climate with any precision is limited. Many coupled human–Earth systems models have been developed to explore potential future energy, emissions, climate and other outcomes of interest. However, in these models the limits to prediction are often addressed through sensitivity analysis, scenarios and model comparisons. In particular, much focus has been on the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) developed for the Intergovernmental Panel on Climate Change (IPCC), taking the ranges of outcomes from these scenarios from different models as indicative of uncertainty<sup>1–5</sup>. While these exercises provide useful insights, they limit the uncertainty space explored by focusing on a limited set of pre-defined socioeconomic and emissions concentration pathways and corresponding climate outcomes, and provide no quantitative probabilistic interpretation<sup>6,7</sup>. With just a range of scenarios or outcomes, decision makers are left to ponder whether all of the scenarios are equally

probable, and whether more extreme outcomes outside the given range are possible. Thus, there are growing calls for more formal probabilistic, risk-based approaches to inform discussions about mitigation and adaptation<sup>8–12</sup>. In coupled human–Earth system analysis, there is value in quantifying both socioeconomic and climate uncertainty in an integrated manner to capture the cascade of uncertainty as more variables are considered along the chain from human activities to emissions to climate, in an attempt to provide insights for further analysis of climate impacts<sup>13</sup>. While there are limits to uncertainty analysis and not all uncertain aspects of our climate future can be quantified, providing transparent quantification where there is a scientific foundation can help work against well-known biases in decision making when uncertainty is present<sup>14</sup>.

There is also a need to regularly update projections of uncertainty as new information becomes available. For example, many studies continue to use the IPCC 8.5 watts per square meter (W per m<sup>2</sup>) scenario (RCP8.5) as a reference no policy baseline. However, given slower

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economic growth, falling costs of low-carbon energy options and government interventions worldwide directed at expanding the role of renewables and limiting emissions, many analysts now believe the RCP8.5 no policy scenario and the heavy use of fossil fuels like coal it implies to be unlikely<sup>8,15–18</sup>. There may be good reasons to still examine RCP8.5 to understand the implications of high consequence, albeit, possibly low probability outcomes. Formal uncertainty analysis can help to provide some indication of the probability of more extreme scenarios based on transparent assessments of underlying uncertainties.

To date, scenario analysis has been the most widely used approach to addressing uncertainty in projections. In general, a scenario approach limits the number of different input assumptions explored and therefore the range of possible outcomes. The set of assumptions explored via scenarios is ultimately a judgment, which may reflect biases or miss important areas of the uncertainty space<sup>19</sup>. Focusing on the results of limited tests can also lead to overconfidence that certain criteria must be met to achieve certain outcomes. Thus, while scenarios can be a helpful tool for investigating and communicating different potential futures, they can also focus attention on a narrow set of pathways, some which may be quite unlikely, which can be counterproductive.

The advantage of uncertainty quantification via a probabilistic Monte Carlo approach is that it more fully and systematically explores the uncertainty space, investigating wide ranges of values for inputs in many different combinations, helping to focus attention on more important regions and providing insight about how likely different outcomes might be<sup>19</sup>. Being transparent about the assumptions behind an uncertainty analysis allows for a clear linking of beliefs about future emissions and their underlying drivers to outcomes and subsequent climate risk analysis, and enables investigation of how differences in those beliefs might change projected outcomes and potential strategies to manage resulting risks.

Despite these benefits, probabilistic approaches also face limitations and challenges (which are discussed in more detail in Supplementary Discussion 1). Judgments must be made regarding the data used to estimate the distributions, the distributional forms, and the correlations between parameters, with the resulting distributions of outcomes depending on those assumptions<sup>19</sup>. There are also limitations related to the interpretation of relationships between outcome distributions that are separately characterized and to structural uncertainty. Scenario discovery approaches<sup>20</sup> can address the former and multi-model analyses can address the latter. The existence of ‘deep’ uncertainties, where information or agreement is insufficient to characterize a distribution, or where processes are so poorly known that they are not represented in the underlying models, also present challenges. Some examples include unknown future carbon-free technologies or destabilization of methane hydrates in permafrost or in the ocean and resulting methane emissions and temperature feedbacks. The exclusion of such possibilities from models means uncertainty analysis conducted using those models does not capture the true tails of outcomes, necessitating complementary what-if analysis. Even for processes that are represented in underlying models, there can be differing views about which uncertainties can be characterized with probability distributions and which are too deep to do so. However, there is room to combine a probabilistic approach with representations of deep uncertainty, for example by generating ensembles conditional on assumptions about deep uncertainties. A number of recent studies have embraced probabilistic projections, even in the presence of deep uncertainties<sup>19,21–24</sup>, in order to provide insight for decision-making.

As long as the limitations and assumptions of uncertainty quantification are made clear, the results of such analyses can provide important insights. There have been a number of valuable uncertainty analyses in the literature focused on global economic development,

emissions and climate, however, they generally focus on a limited set of uncertainties or employ relatively simple models, and many are now quite dated<sup>25–36</sup>. The economic outlook, technology costs, and estimates of Earth system response have changed considerably in recent years with new data, analysis and evidence, making it useful to revisit these uncertainties. Recent work provides useful updates for a few uncertain parameters (population, total factor productivity and climate sensitivity)<sup>9</sup> and uncertainty in long-run economic growth rates<sup>37</sup>. Other newer work has used simple models to make probabilistic projections of emissions<sup>38</sup> or both emissions and global mean temperature change<sup>39,40</sup>.

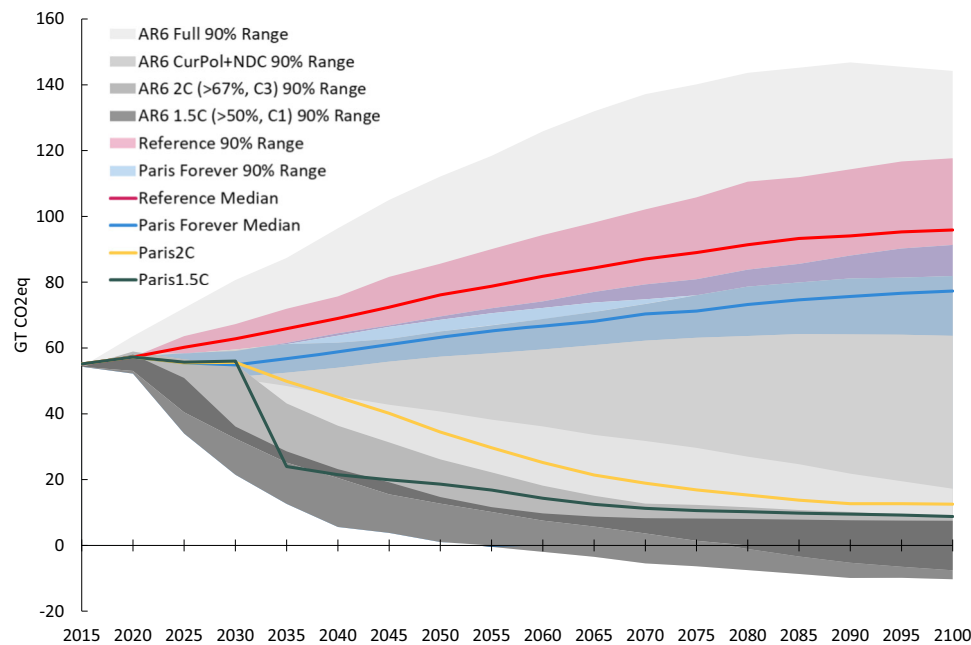
In this work, we take a probabilistic ensemble approach to representing a comprehensive set of both socio-economic and climate uncertainties in a complex human-Earth system model to provide an updated set of probability distributions of both human and Earth system outcomes that can help inform a risk-based decision-making process. This work builds on a previous study focused on socio-economic uncertainties<sup>19</sup> and work using an optimal fingerprint method to assess Earth system uncertainties<sup>41</sup>. We follow earlier studies<sup>29,33,34</sup>, but employ an updated version of the MIT Integrated Global System Model (IGSM), a coupled human-Earth systems model, and a reassessment of uncertainty in input parameters. Analysis of the resulting integrated, probabilistic socio-economic and climate projections shows varying contributions of human and Earth system uncertainties to different climate outcomes and finds that they are not simply additive. We also find that emissions policy lowers the upper tail of temperature change more than the median, policy costs in low- and middle-income economies<sup>42</sup> are more uncertain than in high-income economies, and that renewables are robust investments across a wide range of uncertain futures. This type of uncertainty analysis can inform decision-making about mitigation and adaptation. Chapter 2 of Working Group III of the IPCC's Fifth Assessment Report (AR5) presented a set of approaches, rules and tools for decision-making, many of which would be aided by uncertainty quantification<sup>43</sup>. In particular, the probability distributions from this analysis could be used in formal decision-making under uncertainty analyses that employ expected utility theory, decision analysis, robust decision making or other deliberative methods. However, they can also provide an understanding of uncertainty and risk that can aid decision-makers in more intuitive decision-making processes.

## Results

### Uncertainty quantification via Monte Carlo analysis

Our Monte Carlo-based approach to uncertainty quantification involves developing probability distributions for key input parameters in both the human and Earth system components of the coupled model. These include: climate sensitivity, ocean heat uptake, aerosol forcing, population, labor and capital productivity, autonomous energy efficiency improvement rate, fossil fuel resource availability, advanced technology costs, new technology penetration rates, urban pollutant initial inventories and trends, capital vintaging rate, abatement cost elasticities for methane and nitrous oxide, and elasticities of substitution (labor versus (vs.) capital, energy vs. labor/capital, energy vs. non-energy, inter-fuel substitution, and resource supply elasticities). Estimated distributions for socioeconomic parameters are based on statistical estimates using historical data where possible, published estimates of uncertainty, literature results and expert judgment, with correlations among subsets of related parameters imposed. A joint distribution for Earth system parameters is estimated using an optimal fingerprint approach<sup>41,44,45</sup>. These input distributions may be a useful result of the effort in themselves. See Supplementary Methods 1 for distributions of all input parameters.

We then sample from the distributions, using Latin Hypercube Sampling (LHS)<sup>46,47</sup> to draw samples from each input probability distribution, and imposing a correlation structure amongst subsets of



**Fig. 1 | Total global greenhouse gas emissions over time.** Shown for each ensemble scenario from this study (Reference in magenta, ParisForever in blue, Paris2C in yellow and Paris1.5 C in green; colored shaded areas represent 90% probability bounds and solid colored lines are the medians) compared with

scenarios from the International Panel on Climate Change (IPCC) Sixth Assessment Report (AR6)<sup>5</sup> (in shades of gray; the AR6 Full 90% range spans all the shades of gray).

parameters, using @Risk software in Excel. Next, we generate ensembles of model runs using the sampled parameter values and develop integrated, probabilistic socio-economic and climate projections. These projections provide insight into the probability of outcomes of interest, including emissions, CO<sub>2</sub> concentrations, radiative forcing, temperature, precipitation, Gross Domestic Product (GDP) and energy use. Global climate mitigation policy remains a ‘choice’ variable or a ‘deep uncertainty’ which we explore with four separate policy ensembles. The ensemble scenarios include a no new climate policy reference case (Reference), a case extrapolating Nationally Determined Contribution (NDC) targets of the Paris Agreement (ParisForever), and two policy cases that achieve long-term temperature stabilization targets of 2 °C and 1.5 °C (Paris2C and Paris1.5C). Further details of our approach are described in the Methods section and Supplementary Methods 1.

The distribution of model outcomes from the ensemble of simulations for a particular scenario provides estimates of future states and their uncertainty, conditional on the model structure, the distributions of the uncertain input parameters and their assumed correlations, and the assumed scenario attributes (e.g. policy pathway). To address uncertainty in the form of the underlying input distributions, we also test an alternate setting using uniform distributions for all socio-economic parameters. This follows the approach of robust decision making, which assumes all values are equally likely, defining only the ranges for each parameter from which to sample. We use the 1st and 99th percentiles of our original distributions for the range of the uniform distributions<sup>19</sup>. While changing the distributional form of the inputs does affect the resulting distributions of outputs, the differences are not large and the tails of distributions are affected differently depending on the outcome (see Supplementary Fig. 7). Different assumed correlations between inputs would also affect results, with missing correlations potentially widening the outcome distributions by allowing for a great variety of input sample combinations. For example, capturing regional correlation for labor and capital productivity growth results in more narrow global GDP outcomes than if regional productivity growth was uncorrelated. Correlation

assumptions can have other implications for results as well. For example, uncorrelated technology costs mean that even if one fossil-based (or renewable) technology is not competitive, another might be. If these fossil or renewable costs were correlated, it could lead to overly difficult or easy energy transitions. Given the computational demands of the models we use, we limit the ensemble size to 400 members, which, with Latin Hypercube sampling has been shown to be sufficient<sup>46,47</sup>. We further test the adequacy of this sample size by creating 1000-member ensembles. We find that this does not substantially impact the outcome distributions<sup>19</sup> (see Supplementary Fig. 8).

## Emissions

The variance in emissions is greatest in the Reference scenario, with greenhouse gas (GHG) emissions in 2100 ranging from about 76 to 118 gigatonnes of CO<sub>2</sub>-equivalent (Gt CO<sub>2</sub>eq) for the 5th to 95th percentile, with a median of 96 Gt. The range of Reference emissions is shifted down compared to the high end of the full range of emissions from the IPCC Sixth Assessment Report (AR6)<sup>4</sup> (Fig. 1). While our Reference case does not include the mitigation pledges made by the countries in their submissions under the Paris Agreement, it does include policies targeting an expansion of renewables in power generation consistent with the International Energy Agency (IEA)<sup>48</sup>, which have resulted in lower renewable technology costs and a slowing rate of emissions growth over the last decade. The Economic Projection and Policy Analysis (EPPA) model (the human system component of the MIT IGSM) employed here also reflects slower prospects for long-term regional economic growth (particularly for China).

The three policy scenarios reduce or effectively eliminate emissions uncertainty as policies are implemented in the model as emissions caps that must be met. The 90<sup>th</sup> percentile range for ParisForever 2100 emissions is 64–91 Gt CO<sub>2</sub>eq, with a median of 77 Gt. NDC targets specified as reductions from reference emissions or as emissions intensity goals leave some room for uncertainty in emissions projections due to the nature of the policies imposed and the underlying uncertainty in emissions growth. In 2100, median emissions in

ParisForever are about 19% lower than median 2100 emissions in Reference. Median 2100 emissions in Paris2C and Paris1.5C are 13 Gt and 9 Gt, respectively, which is 87% and 91% below median 2100 Reference emissions. The emissions constraints are binding in all cases in the Paris2C and Paris1.5C policy ensembles, so there is effectively no uncertainty in global emissions under those scenarios.

However, there is uncertainty about how those emissions are distributed across regions, sectors and greenhouse gases since emissions trading is allowed. These distributions depend on the cost of abatement opportunities, which change with different sampled values of input parameters. The greatest variance in regional emissions is in China, and the greatest variance in sectoral emissions is in the electricity and industry sectors (see Supplementary Figs. 9–10). Sectoral results also suggest that there are limited abatement opportunities in the agricultural, residential and industrial sectors. This reflects challenges in those sectors, where good options for reducing or eliminating emissions have yet to be identified.

Due to the many unresolved issues (e.g., cost, public acceptance, ability to operate sustainably and at scale) related to negative emission technologies (NETs) such as biomass electricity with carbon capture and storage (BECCS), direct air capture (DAC) and afforestation, we did not include these technologies in this study. However, we have explored their role in other studies<sup>49–52</sup>, and if available and scalable at reasonable cost, NETs could reduce the need for near-term emissions reductions, but in turn risk exceeding temperature targets if they cannot be scaled up<sup>53,54</sup>.

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 meeting this goal would require NETs 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 even achieving net zero emissions. As emphasized in the IPCC, it is the cumulative budget over the century that matters for temperature outcomes<sup>4,55</sup>. 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. This results in very high costs even in the early years since 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<sup>55–57</sup>. 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 simulations of the MIT Earth System Model (MESM) component of the IGSM is nearly identical to the value used in the IPCC Special 1.5°C Report<sup>55</sup>. However, the 90% probability range of the TCRE from the estimates we use<sup>41</sup> 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 is similar to that shown by IPCC Special 1.5°C Report<sup>55</sup>, while the allowable budget for the 33%/66% probability is 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 in MESM. Compared with most IPCC scenarios, we have lower non-CO<sub>2</sub> GHG emissions and somewhat higher SO<sub>2</sub> emissions resulting in greater negative aerosol forcing, both of which allow for more CO<sub>2</sub> emissions. As a result, our carbon emissions (relative to 2017) are near the high end of the range reported by Rogelj et al.<sup>56</sup>. It is important to note that IPCC carbon budget studies generally make exogenous assumptions about non-CO<sub>2</sub> GHGs and then find the resulting remaining CO<sub>2</sub> budget. In contrast, our approach dynamically determines the most cost-

effective balance of reductions across all GHGs (using global warming potentials, GWPs, as weights).

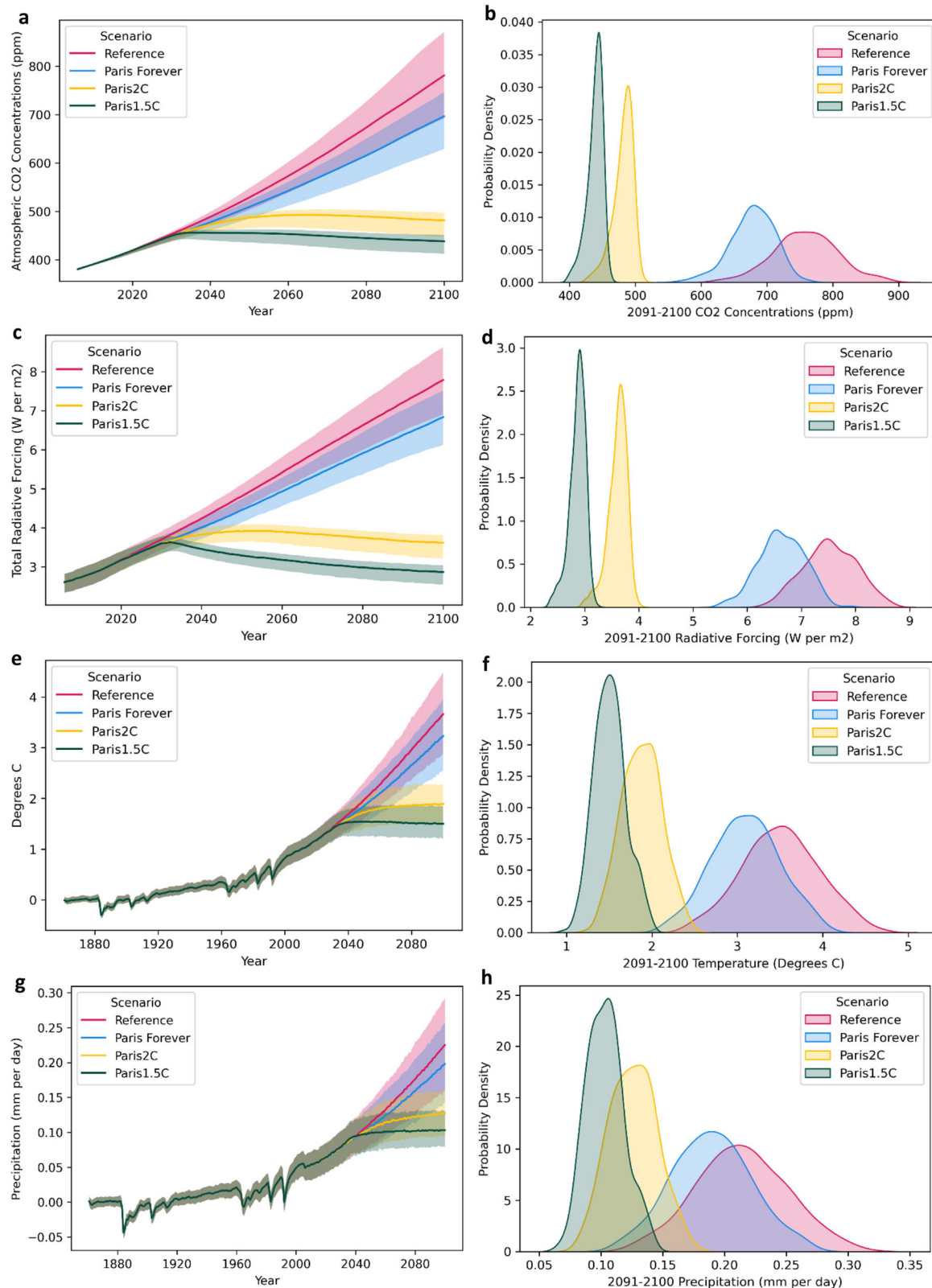
## Atmosphere and climate

Over the period from 2020 to 2100, the Paris2C and Paris1.5C scenarios have a smaller 90% range of CO<sub>2</sub> concentrations and of total radiative forcing (which is the sum of the effects of all long-lived greenhouse gases plus tropospheric ozone and aerosols) compared to the Reference and ParisForever scenarios due to their fixed emissions constraints (Fig. 2a, c). 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 (as in the Reference and ParisForever scenarios), the range of concentrations is wider, with the Reference scenario having the widest range. The uncertainty in radiative forcing is driven by: (1) varying concentrations, and (2) uncertainty in the strength of sulfate aerosol forcing. Moving from Reference to ParisForever to Paris2C, the distributions of end-of-century concentrations and radiative forcing become increasingly asymmetric, with policy (implemented as an emissions cap achieved with certainty) trimming the upper tail more than the lower tail (Fig. 2b, d). Paris1.5C is slightly less skewed than Paris2C. In 2100, the 90% bounds of CO<sub>2</sub> concentrations are 692–871 ppm for Reference, 629–747 ppm for ParisForever, 448–497 ppm for Paris2C and 412–451 ppm for Paris1.5C. For total radiative forcing, those 90% bounds are 6.9–8.6 W per m<sup>2</sup> for Reference, 6.1–7.5 W per m<sup>2</sup> for ParisForever, 3.2–3.8 W per m<sup>2</sup> for Paris2C and 2.5–3.0 W per m<sup>2</sup> for Paris1.5C. We find that there is a ~8% chance that emissions will be high enough to achieve 8.5 W per m<sup>2</sup> in 2100, supporting the concern of some analysts that it no longer should be considered a central estimate in the absence of additional policy<sup>8,15–18</sup>. However, scenarios as high as this or higher are still possible in our analysis and, hence, relevant for evaluating the expected damages.

As with concentrations and radiative forcing, policy also lowers the upper tails for temperature and precipitation (Fig. 2e, f). Uncertainty in temperature outcomes are driven by varying concentrations and radiative forcing (which in turn are driven by uncertainty in carbon uptake and aerosol forcing), along with uncertainty in ocean heat uptake and overall climate sensitivity (Earth system response to higher emissions). 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. 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 Reference temperature change aligns well with IPCC's AR6 projections<sup>4</sup> for the SSP3-7.0 scenario, which yields end-of-century median and very likely (90–100%) estimates of 3.6°C and 2.8–4.6°C, respectively. ParisForever is similar to AR6's SSP2-4.5 scenario (median of 2.7°C; very likely range of 2.1–3.5°C), while Paris2C is similar to SSP1-2.6 (median of 1.8°C; very likely range of 1.3–2.4°C) and Paris1.5C is similar to SSP1-1.9 (median of 1.4°C; very likely range of 1.0–1.8°C) (see Supplementary Table 5).

However, importantly, the AR6 estimates are based on the range of estimates of different runs from different models, not an uncertainty quantification effort designed to generate probability distributions of temperature outcomes based on emissions. There are limited studies that have done the latter. Gillingham et al.<sup>9</sup> conducted a multimodal uncertainty quantification exercise and found median temperature resulting from baseline (no climate policy) trajectories to be 3.79°C, with a 90% range of 2.53–5.48°C. A study using the Kaya Identity and IPCC's relationship between cumulative CO<sub>2</sub> emissions and temperature to develop a probabilistic forecast of temperature change to 2100 found a median of 3.2°C and a 90% range of 2.4–4.9°C, assuming continuation of current trends (i.e. no climate policy)<sup>39</sup>. Older studies tended to project higher temperature changes in the absence of policy—for example, a median of 5.69°C and 90% range of





**Fig. 2 | Global-average climate outcomes over time and frequency distributions in 2091–2100. a, b** Carbon dioxide (CO<sub>2</sub>) concentrations in parts per million (ppm), **(c, d)** total radiative forcing (relative to 1861–1880) in watts per square meter (W per m<sup>2</sup>), **(e, f)** surface air temperature (relative to 1861–1880) in degrees Celsius (C), and

**(g, h)** precipitation (relative to 1861–1880) in millimeters (mm) per day. Shown for each ensemble scenario (Reference in magenta, ParisForever in blue, Paris2C in yellow and Paris1.5C in green; shaded areas represent 90% probability bounds; lines are the medians).

**Table 1 | Percent of ensemble runs exceeding a given temperature**

		% of runs exceeding temperature			
		Reference	Paris Forever	Paris2C	Paris1.5C
Temperature (°C)	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%	...	...	...

Temperature thresholds are defined as the average global surface air temperature in 2091–2100 relative to 1861–1880 in degrees Celsius (°C). 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 given 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. The three dots indicate that a cell has the same value as the cell above it.

4.02–7.96 °C<sup>33</sup>. However, government interventions worldwide, falling costs of low-carbon technologies and slower economic growth over the last decade have reduced estimates of emissions and, in turn, temperature change under a no climate policy scenario.

At a global scale, the uncertainty in precipitation change can be directly associated to the uncertainty in average surface-air temperature change. Higher surface-air temperatures strengthen potential evapotranspiration (across ocean surfaces and land soil-vegetation systems) and in doing so, accelerate the hydrologic cycle. Thus, at a global scale, increasing (or reducing) near-surface warming results in larger (or smaller) increases in evapotranspiration to support the associated precipitation increases. By the end of the century, global precipitation increases by 0.15–0.28 mm per day (90% range) for Reference, 0.13–0.24 mm per day for ParisForever, 0.10–0.16 mm per day for Paris2C and 0.08–0.13 mm per day for Paris1.5C (Fig. 2g, h).

Importantly, an emissions cap 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 one of the greatest roles of climate policy—to lower (or effectively eliminate) the chance of extreme temperature outcomes. This is highlighted in Table 1, which shows how the percentage of runs exceeding given temperature levels varies across the ensemble scenarios. Results indicate that even relatively modest emissions cap policies can substantially reduce the probability of dangerously high temperature outcomes. For example, the ParisForever scenario has modest emissions reductions relative to the Reference (see Fig. 1), yet greatly reduces the chance of temperature changes above 4 °C (decreasing it from 15% to <0.25%). For the Paris2C and Paris1.5C scenarios, temperature is essentially bound at 2.5 °C and 2 °C, respectively, with less than 0.25% of runs exceeding those levels. Other policy measures, such as carbon pricing or intensity targets, that do not necessarily place an absolute limit on emissions could have a more symmetric effect on the distribution. Also important are the lower tails of the temperature change distributions. As seen in Fig. 2e, under Reference and ParisForever, the 2 °C temperature target is exceeded for all ensemble members.

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 substantial 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 important 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.

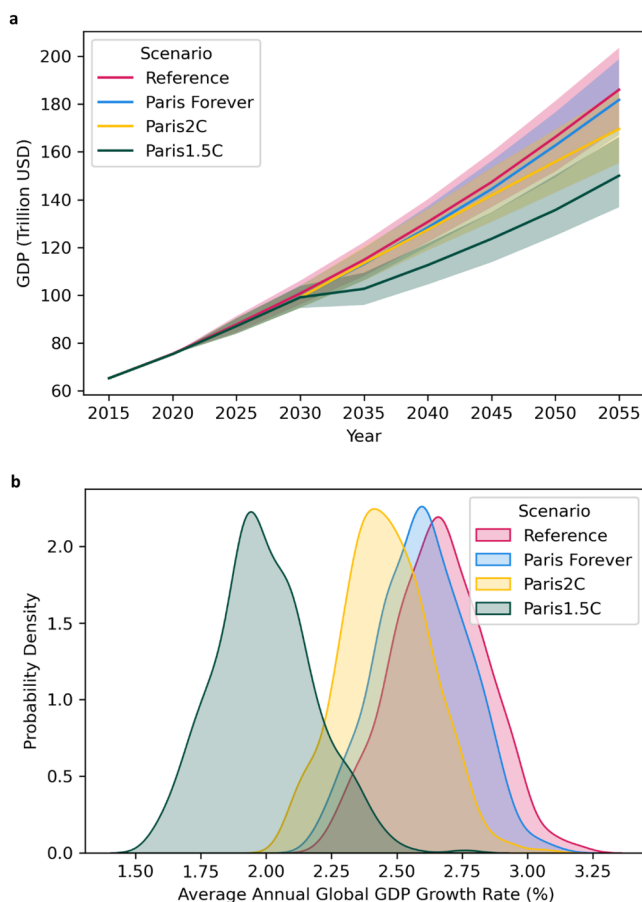
## Economy

For all ensemble scenarios, GDP is endogenously determined in the model and therefore uncertain. In this particular approach, the impacts of climate change on the economy are not included. For example, if climate change caused damage to the economy, energy use and emissions might be reduced, making it less likely that such large increases in temperatures were actually possible<sup>58</sup>. On the other hand, high temperatures are likely to increase the demand for air conditioning and energy, and if that energy is from fossil fuels, the result would be an increase in emissions and a positive feedback on warming. Similarly, climate damage to agricultural yields might require more land under cultivation, more fertilizer, and more livestock, and result in more deforestation and more carbon dioxide, methane, and nitrous oxide emissions. Natural feedbacks, such as increased forest growth from higher ambient CO<sub>2</sub>, or changes in forest and land productivity, and natural sources of methane and nitrous oxide due to changes in temperature precipitation are included in the Earth system component of the model. Including climate change impacts on the economy would also affect the relative economic impact of different policy scenarios, however, notably, the benefits of reduced damages from climate change are not included.

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 abatement and technology costs of doing so, varies. Here we focus on GDP results through 2050. Relative to 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 (Fig. 3a). This highlights the additional reduction in GDP of achieving 1.5C vs. 2C (but we caution that our analysis does not include the climate damages to GDP avoided by these stricter policies). In all scenarios, GDP is growing, with median GDP in 2050 ending up 2.2 times higher (2.2x) 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 (Fig. 3b), 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%), and 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 global economic growth. The GDP impacts of policy could be lowered further by the availability of additional mitigation options, such as negative emissions technologies (NETs), which, as noted earlier, are not included in the modeling here. In particular, under the Paris1.5C scenario, the availability of NETs in the second half of the century would provide headroom for more near-term emissions, allowing for a more gradual energy transition and lower economic impact.

We also project regional economic growth across the policies, which is conditional on assumptions about the regional emissions allocations imposed. Here, we first determined a global carbon price



**Fig. 3 | Economic outcomes.** **a** Global Gross Domestic Product (GDP) 2020–2050 in trillion U.S. Dollars (USD), **(b)** frequency distributions of average annual global GDP growth from 2020 to 2050. Shown for each ensemble scenario (Reference in magenta, ParisForever in blue, Paris2C in yellow and Paris1.5C in green; shaded areas represent 90% probability bounds; lines are the medians).

trajectory starting in 2030 and increasing at 4% per year that, given median socio-economic parameter values, resulted in global emissions pathways consistent with the temperature targets. Assuming a 4% discount rate, this results in a constant present value carbon price, consistent with minimizing the net present value policy cost. This approach results in regional emissions trajectories that ensure marginal abatement costs in each region are equal to the global carbon price at median values for all input parameters. 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 emissions trading systems. This procedure implies that under the emissions caps with median parameter settings, there is no emissions trading among regions. However, uncertain economic growth, technology costs and resource availabilities across regions mean that, within a given ensemble, regions will be net allowance buyers in some simulations and net sellers in others, and their net trading position may change over the timeframe of the simulation. The neutral assumption of no net trading under median parameter settings provides a starting point from which one might consider financial transfers or mechanism designs that could achieve more equitable outcomes.

For this setting, we find wide variation in GDP growth impacts across regions under the scenarios. For some regions, like the United States and Europe, the scenarios largely overlap, meaning the policies have a relatively small impact on GDP (Fig. 4). However, for other countries, such as China and India, and even more so for regions like

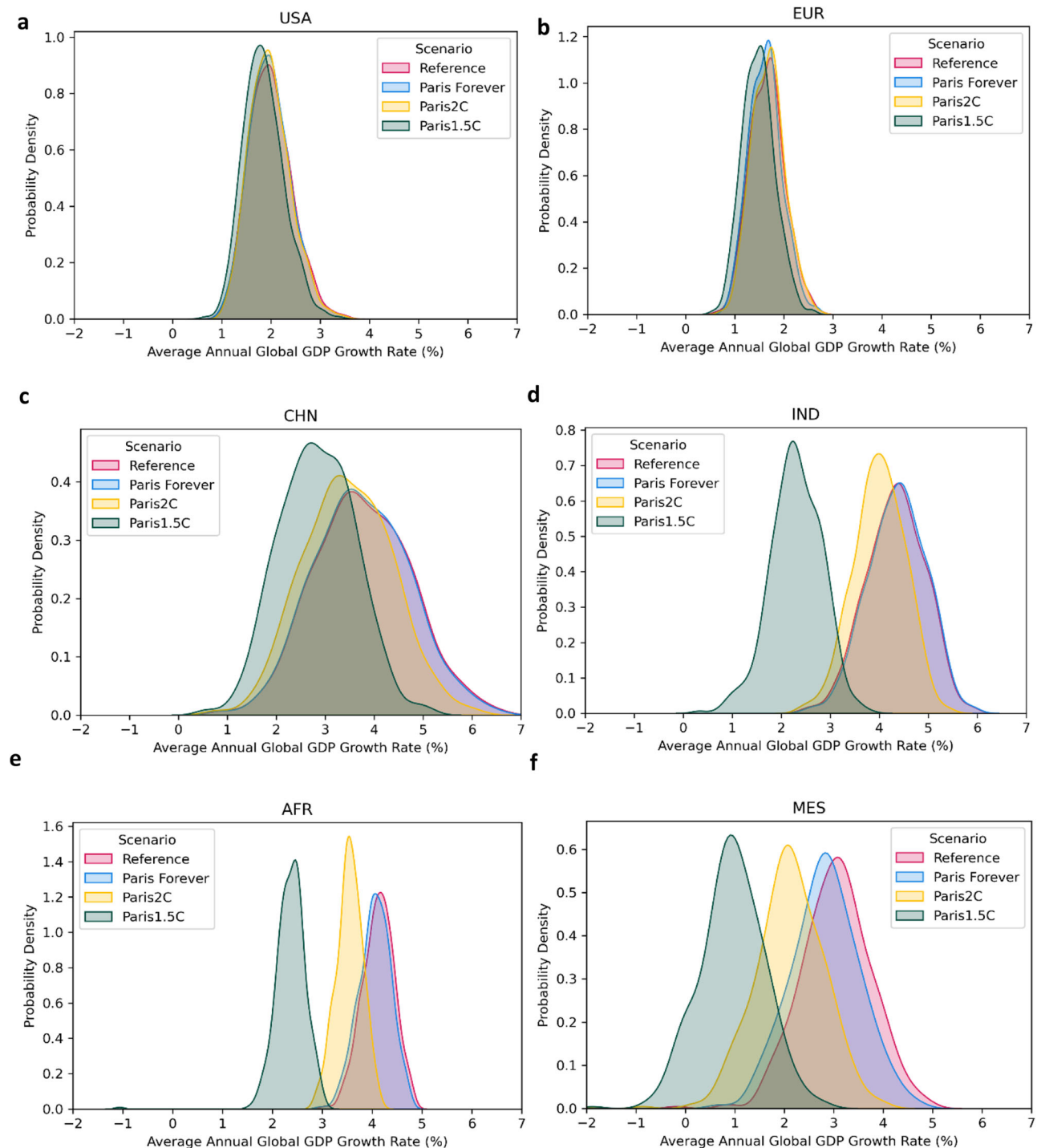
the Middle East and Africa, GDP under the 2C and 1.5C policies increasingly diverges from the Reference and ParisForever scenarios, reflecting higher policy costs. For policy costs, measured as the difference in average annual GDP growth between a policy scenario and the Reference scenario (the difference between distributions in Fig. 4), uncertainty tends to be higher for low- and middle-income economies than high-income economies. For Africa, even though the GDP growth rate within each scenario is less uncertain than other regions (due to it being a large aggregated region), the policy costs are more uncertain than the United States and Europe. For example, under the 2C policy, the policy impact on the average annual GDP growth rate in the United States ranges from a growth rate increase of 0.03 percentage points (5<sup>th</sup> percentile) to a rate decrease of 0.05 percentage points (95<sup>th</sup> percentile). For Africa under 2C, the 90% range spans a growth rate decrease of 0.46–0.76 percentage points. This result highlights the very important issue of equity among countries, especially between higher-income countries where the economies are now less energy-intensive, and low-income countries still in a relatively energy-intensive stage of growth. The results show developing countries as likely to bear the greatest costs of global climate mitigation unless specific actions are taken to avoid that outcome. With a global cap and trade policy, allowance allocation can be used to facilitate financial transfers to achieve more equitable outcomes. However, with uncertainty in growth and other factors, determining an allowance allocation that would achieve a given level of transfer would be a challenge.

### Energy

Not surprisingly, our results indicate that an energy transition away from fossil fuels is required in order to achieve the long-term temperature goals of the Paris Agreement. This is achieved in our scenarios by a combination of switching to low-carbon energy sources and by reducing the amount of energy used in both production and consumption (which is driven in turn by the ease of substituting energy for non-energy inputs to production and consumption). The fossil share of total global primary energy falls from 2020 levels (88%) in all scenarios, but 2100 shares are dramatically larger in Reference and ParisForever (79% and 76% medians) compared to Paris2C and Paris1.5C (26% and 23% medians) (see Supplementary Fig. 11).

As fossil energy is phased down under stringent climate policy, other low-carbon energy sources take its place. Figure 5 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 carbon capture and storage (CCS)), natural gas (with or without CCS), oil, bioenergy, renewables (wind and solar), nuclear and hydro (hydro is not shown in Fig. 5 as it is modeled as a fixed resource so there is virtually no uncertainty around its deployment). The amount of primary energy from each of these sources is uncertain. Notably, Reference and Paris2C diverge substantially for coal, gas and oil without CCS. Under Reference all three fossil energy sources continue to grow throughout the century from 2015 levels. Under Paris2C, fossil levels are only somewhat lower in 2030 than under Reference, but they decline over time, increasingly diverging from Reference levels. 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 incentive for them, but there is some potential for CCS under Paris2C in the second half of the century.

In terms of energy investment decisions made 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 and across a broad range of potential socioeconomic futures, including



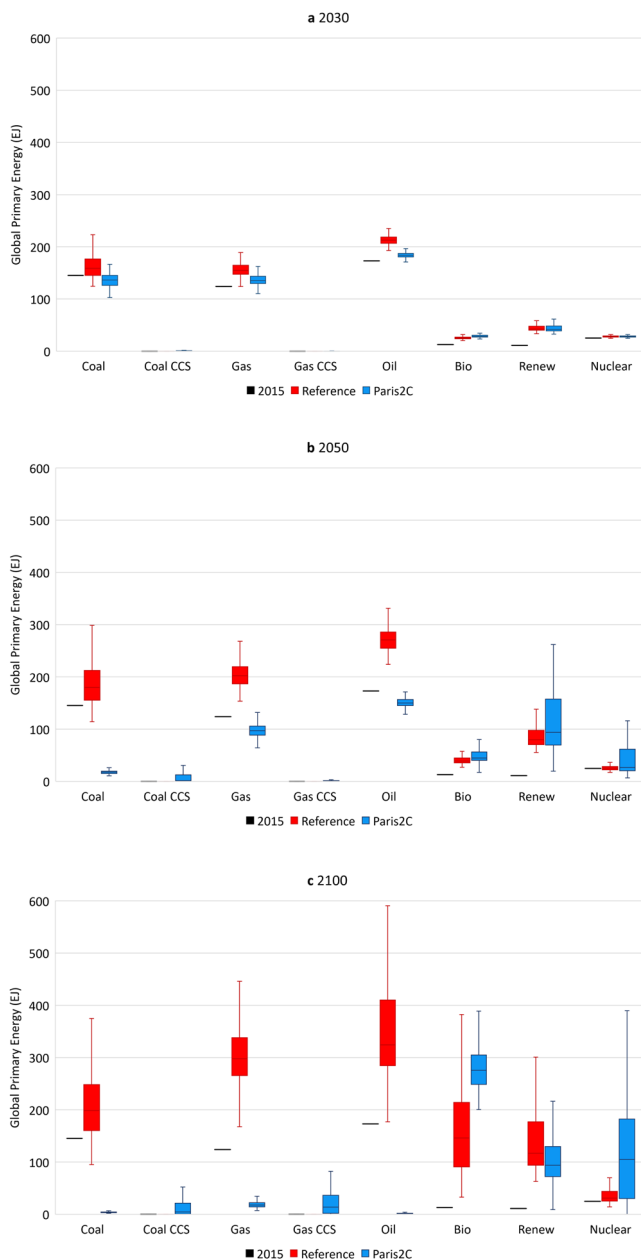
**Fig. 4 | Average annual gross domestic product (GDP) growth rate from 2020 to 2050 for selected regions. a** United States (USA), **(b)** Europe (EUR), **(c)** China (CHN), **(d)** India (IND), **(e)** Africa (AFR) and **(f)** Middle East (MES). Shown for each

ensemble scenario (Reference in magenta, ParisForever in blue, Paris2C in yellow and Paris1.5C in green; shaded areas represent 90% probability bounds). Note: scales differ for each panel.

different assumptions about technology costs. Based on our assessment of the probability distributions of the cost of different technologies, while the scale of competing technologies (such as nuclear, CCS or bioenergy) does vary across ensemble members, a sizable role of renewables is quite robust across the different cost assumptions. In contrast to the AR6<sup>4</sup>, which shows more renewables in the policy cases, in our results renewables end up somewhat lower in 2100 in Paris2C than in Reference, although their share of energy use is higher, because energy and electricity use are lower under stringent policy due to a

greater efficiency response to policy and overall economic consumption being lower. 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. Expanding 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, with the large uncertainty range largely driven by China.





**Fig. 5 | Box and whisker plots of global primary energy by source under Reference (red) and Paris2C (blue) ensemble scenarios. a 2030, (b) 2050, and (c) 2100.** The 2015 emissions are shown in black as a point of reference. The boxes are the interquartile range (25th–75th percentile), with the center line showing the median, and the whiskers extend up to 1.5 times the interquartile range. These statistics are based on 400 sample model runs ( $n = 400$ ) for the Reference scenario and 400 sample model runs ( $n = 400$ ) for the Paris2C scenario. CCS stands for carbon capture and storage; Bio stands for modern biomass energy (liquid- or electricity-based); Renew stands for renewables (wind and solar).

### Relative role of socioeconomic and Earth system uncertainties in climate projections

Efforts to partition climate projection uncertainty<sup>59,60</sup> have found that internal variability and uncertainty in the climate system and modeling of it are the largest drivers in the near-term. However, beyond the next decade or two, uncertainty in human systems and resulting emissions becomes an increasingly important contributor to uncertainty in climate change projections. Climate system uncertainty remains important, but the influence of socioeconomic-driven scenario uncertainty grows over time, and becomes the largest source of uncertainty after

50–100 years<sup>59</sup>. However, different approaches to estimate underlying climate and socioeconomic uncertainty can give widely varying estimates of uncertainty in scenarios, leading to different assessments of how different sources of uncertainty contribute to the overall uncertainty in climate outcomes.

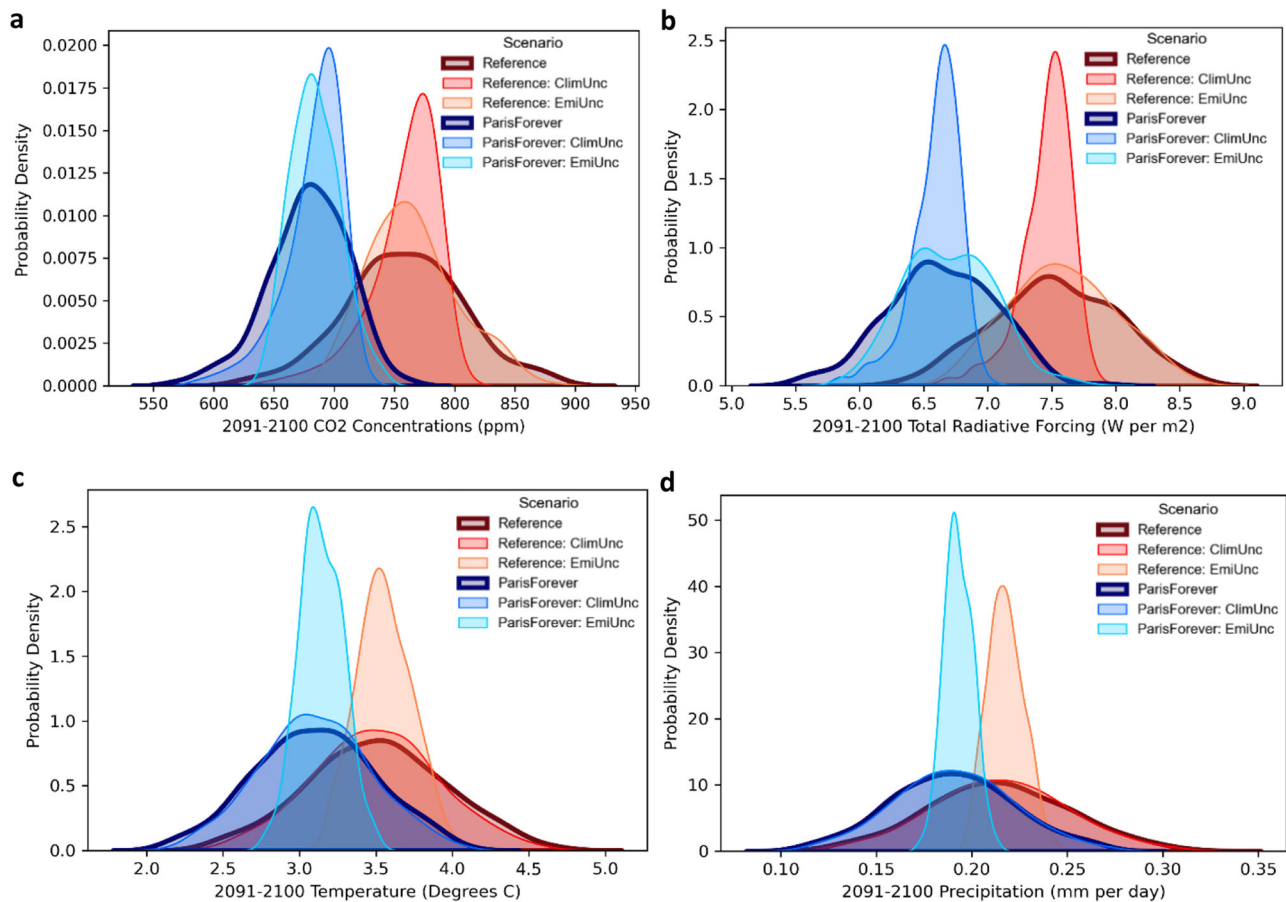
It is also essential to understand that different sources of uncertainty (and related risks) can interact with one another. Terms such as cascading, propagating and compounding have been used in literature to describe the interacting uncertainties and risks related to climate change<sup>61–68</sup>. If uncertainties were simply additive, it would seem that uncertainty would grow unbounded. However, in our analysis, uncertainty ranges do not grow in an unbounded fashion as more uncertainties are considered, as many of the sampled uncertainties end up offsetting one another.

Uncertainty in the global climate outcomes presented above for Reference and ParisForever scenarios are driven by parametric uncertainties in both the socioeconomic system, which drives emissions, and the Earth system, which drives climate responses to emissions. To explore the relative contribution of socioeconomic/emissions uncertainty and climate-response uncertainty, we compare the distributions from the full ensembles (both socioeconomic/emissions and climate-response uncertainty, thick lines in Fig. 6) to those from two different ensemble variations: (1) ensembles with only Earth system uncertainty, with emissions held at the median level (ClimUnc), and (2) ensembles with only socioeconomic variables and resulting emissions uncertain, with climate-parameters held to their median values (EmiUnc). Figure 6 compares the end-of-century (2091–2100) frequency distributions. A visual comparison of the ClimUnc and EmiUnc distributions can quickly reveal the relative contribution of uncertainties in socioeconomic and Earth system response. More formally, we can compare dispersion metrics for the distributions—here we focus on the mean absolute deviation (MAD) summarized in Table 2, but also calculate the inter-quartile range (IQR) and the range between the 5th and 95th percentiles (see Supplementary Table 6). Figure 7 shows the ratio of MAD for the distributions with only one source of uncertainty relative to MAD for the distributions with both uncertainties over time for the Reference ensemble. These MAD ratios reflect how much of the dispersion in the full uncertainty distribution is captured by only one source of uncertainty (either emissions or climate).

For CO<sub>2</sub> concentrations, uncertainty due to emissions is greater than uncertainty due to climate by the end of the century, especially for the Reference ensemble (Figs. 6a and 7a). However, climate uncertainty plays an important role as well—even when emissions are certain (as in ClimUnc), there is considerable uncertainty in concentrations because of uncertainty in ocean and land uptake of CO<sub>2</sub> as well as natural sources of other gases because of their dependence on climate. When emissions are more tightly controlled (as in the ParisForever policy scenario), then climate uncertainty becomes relatively more important. At the end of the century the MAD ratio is 0.77 for EmiUnc and 0.56 for ClimUnc under Reference. The corresponding values under ParisForever are 0.62 and 0.72. While climate uncertainty begins as more important, the importance of emissions uncertainty to uncertainty in CO<sub>2</sub> concentrations grows over time, surpassing climate uncertainty by 2070 in the Reference scenario (Fig. 7a).

Emissions uncertainty becomes even more important for total radiative forcing (Figs. 6b, 7b) because forcing is also affected by uncertainty in other greenhouse gases and aerosols, such as sulfates (from SO<sub>2</sub> emissions) and black carbon. At the end of the century the MAD ratios for EmiUnc and ClimUnc, respectively, are 0.87 and 0.38 under Reference and 0.85 and 0.43 under ParisForever. We again see climate uncertainty as more important in early decades, but the importance of emissions uncertainty to uncertainty in total radiative forcing grows quickly, surpassing climate uncertainty by 2060 (Fig. 7b).

However, that pattern is not seen for temperature (Figs. 6c, 7c) and precipitation (Figs. 6d, 7d)—for those outcomes, uncertainty due



**Fig. 6 | Impact of climate and emissions uncertainties on climate outcomes.** Frequency distributions for global-average climate outcomes in 2091–2100 for Reference and ParisForever ensembles with emissions uncertainty plus median climate (EmiUnc, orange for Reference and light blue for ParisForever) vs. ensembles with median emissions plus climate uncertainty (ClimUnc, red for Reference and blue for ParisForever) vs. ensembles with both emissions and climate

uncertainty (dark blue for Reference and dark red for ParisForever): (a) carbon dioxide ( $\text{CO}_2$ ) concentrations in parts per million (ppm), (b) total radiative forcing (relative to 1861–1880) in watts per square meter ( $\text{W per m}^2$ ), (c) surface air temperature (relative to 1861–1880) in degrees Celsius (C), and (d) precipitation (relative to 1861–1880) in millimeters (mm) per day.

to climate is greater than uncertainty due to emissions throughout the century. For end-of-century temperature, the MAD ratios for EmiUnc and ClimUnc, respectively, are 0.40 and 0.90 under Reference and 0.36 and 0.91 under ParisForever. For end-of-century precipitation, the role of climate uncertainty is even stronger: the MAD ratios for ClimUnc are 0.95 and 0.96 under Reference and ParisForever, respectively. The corresponding values for EmiUnc are 0.26 and 0.24. The greater effect of climate uncertainty on temperature and precipitation is not 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, and precipitation outcomes are heavily driven by temperature.

Importantly, we find that emissions and climate uncertainty are less than additive—for each climate outcome, the dispersion metrics for the distributions with both emissions and climate uncertainty are less than the sum of climate uncertainty alone (ClimUnc) and emissions uncertainty alone (EmiUnc) (see Table 2 and Supplementary Table 6). Focusing on uncertainty in temperature projections in Figs. 6c, 7c, for example, the combined effect of uncertainty in climate and emissions is almost identical to climate uncertainty alone—adding emissions uncertainty barely changes the overall uncertainty. However, there is still considerable temperature uncertainty resulting from emissions uncertainty alone. These results indicate that cascading uncertainties are not necessarily additive, and capturing more

uncertainties does not automatically widen the uncertainty range of outcomes because uncertainties can offset one another. This illustrates the need for an integrated modeling system for uncertainty analysis as it is unclear how to combine separate analyses of Earth system uncertainty and human system uncertainty. An assumption that such analyses are additive would be misleading.

These results may appear to contradict the results of Lehner et al.<sup>59</sup>, which finds uncertainty in human systems and resulting emissions (what they call scenario uncertainty) to be the predominate driver of temperature change uncertainty by the end of the century, since Figs. 6 and 7 shows climate uncertainty as dominating the end-of-century temperature uncertainty in both of the ensembles. However, a major reason for this is that uncertainties in our analysis are conditional on policy assumptions (i.e. whether the near-term Paris targets are met or not). Results from Lehner et al.<sup>59</sup> are not conditional on policy but are based on sets of emissions scenarios that span both scenarios with no policy and those that at least implicitly have different policy outcomes. Still, the time evolving contribution of uncertainty follows the same general pattern of Lehner et al.<sup>59</sup>—climate response uncertainty dominating at least the first few decades, but emissions scenario uncertainty generally becoming more important over time (Fig. 7).

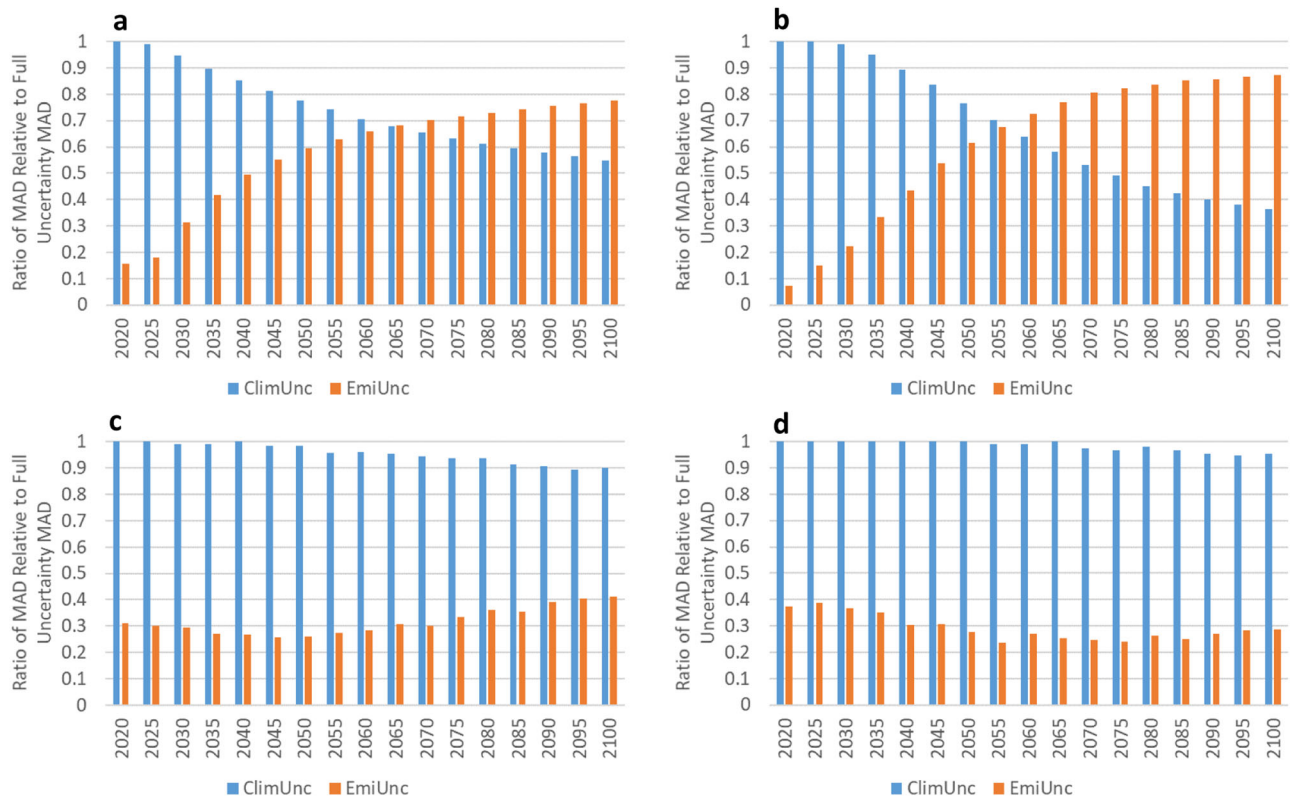
## Discussion

Uncertainty is unavoidable in economic, energy and climate projections. However, with advances in understanding of underlying

**Table 2 | Summary of mean absolute deviation (MAD) for the ensembles**

	Reference				ParisForever			
	All	ClimUnc	EmiUnc	Sum of ClimUnc & EmiUnc	All	ClimUnc	EmiUnc	Sum of ClimUnc & EmiUnc
<b>CO<sub>2</sub> Concentrations</b>	38.83	21.84	29.81	51.65	26.46	18.94	16.52	35.47
<b>Total Radiative Forcing</b>	0.39	0.15	0.34	0.49	0.34	0.15	0.29	0.44
<b>Temperature</b>	0.36	0.32	0.14	0.47	0.32	0.29	0.12	0.40
<b>Precipitation</b>	0.030	0.028	0.008	0.036	0.026	0.025	0.006	0.031

MAD for distributions with full uncertainty (both climate and emissions uncertainty) is less than the sum of MAD for *ClimUnc* and *EmiUnc* distributions, meaning socioeconomic and climate uncertainties are not simply additive.



**Fig. 7 | Mean absolute deviation (MAD) of climate-only uncertainty (ClimUnc, blue) and emissions-only uncertainty (EmiUnc, orange) distributions relative to full uncertainty (both climate and emissions uncertainty) distribution over time.** For the Reference ensemble for: (a) carbon dioxide (CO<sub>2</sub>) concentrations, (b) total radiative forcing (relative to 1861–1880), (c) temperature (relative to

1861–1880), and (d) precipitation. Ratios are calculated as: MAD for ClimUnc distribution divided by MAD for the full distribution with both climate and emissions uncertainty and MAD for EmiUnc distribution divided by MAD for the full distribution.

socioeconomic factors and Earth system responses, updated estimates of uncertainty can help inform mitigation and adaptation decisions. This paper presents a consistent framework for uncertainty quantification in a complex coupled human-Earth systems model, which facilitates a broad exploration of global-change uncertainty and provides a probabilistic interpretation of both socioeconomic and climate outcomes. This probabilistic analysis can support a risk management approach to decisions in response to global climate change.

The Paris Agreement set a goal of limiting global average surface temperature warming to well below 2 °C, and to attempt to meet a 1.5 °C target. These temperature targets are often translated into radiative forcing, concentrations, or emissions targets or budgets. Typically, the relationships between socioeconomic factors, emissions, concentrations, radiative forcing and temperature are expressed in models without uncertainty. Here we account for uncertainty in those relationships, exploring the degree to which a given emissions

trajectory can be expected to meet a proposed climate target. The application illustrates that, if a certain temperature target is to be met, emissions constraints will need to be adjusted over time as uncertainty in the climate system is further resolved.

Our results show that a climate policy emissions cap lowers the upper tail of the temperature change 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 95th percentile is reduced by 2 °C (from 4.3 °C to 2.3 °C), illustrating the value of climate policy in lowering the chances of high temperature outcomes. We also show that Earth system and socioeconomic uncertainties have a less than additive impact on the range of outcomes in terms of mean absolute deviation and other metrics of dispersion, as uncertainties can offset one another to varying degrees depending on the outcome of interest. Earth system uncertainties dominate end-of-century temperature uncertainty while human system uncertainties dominate

radiative forcing uncertainty, reflecting the uncertainty in translating radiative forcing to temperature. We further find that, even under a stringent climate policy designed to meet 1.5 °C, the global economy continues to grow, but that burden sharing issues remain as policy costs vary across regions, with greater uncertainty generally occurring in low- to middle-income economies. In terms of the future energy system, there are many patterns of energy and technology development consistent with long-term environmental pathways, and the distributions provide information for assessing risks of investing in different technologies. In particular, renewable energy sources are expected to expand substantially regardless of the level of future policy and across a broad range of socioeconomic futures.

This uncertainty quantification approach can also guide future research and model development efforts. It can identify the key components and assumptions in models, and the uncertainties of greatest importance or least understanding, thus highlighting areas that warrant the most attention. Further research should consider the implications of including additional abatement options (e.g. for agriculture, industry and residential sectors, negative emissions technologies and electrification pathways), alternative regional emissions allocations, and climate and other environmental feedbacks on the economic system. Importantly, further research is needed to better resolve the low-probability tails of distributions, including assessment of potentially unmodeled processes that could lead to extreme outcomes. Combining probabilistic and deep uncertainty methods to better understand low-risk, high-consequence outcomes and their implications for decision-making is an important area of future work.

Further, this approach can guide future scenario development. Whereas standardized scenarios constrain the uncertainty space explored, this probabilistic ensemble approach can give a more comprehensive view of uncertainty. Scenarios (and sensitivity tests) can be developed that connect to the distributions of inputs and/or outputs. The ensemble results can also be utilized with scenario discovery techniques<sup>19,20</sup> to identify conditions consistent with outcomes of interest (e.g., salient tipping points, large socio-environmental inequities or particular energy or economic outcomes). This approach can also provide insights into how multiple uncertainties interact and the relative human vs. Earth system contributions to uncertainty in climate-related outcomes.

## Methods

### Model

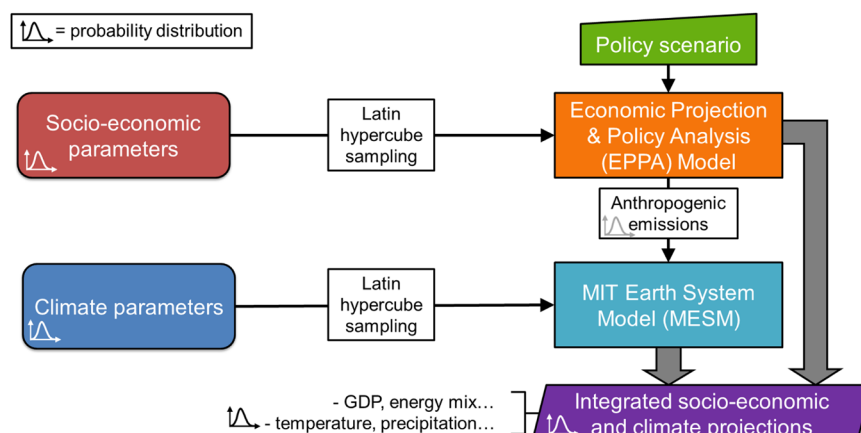
Coupled human-Earth systems models allow for consideration of both socio-economic and climate uncertainties. Here we use the MIT Integrated Global System Model (IGSM) framework, which links the

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<sup>69–71</sup> (see Supplementary Fig. 12). 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<sup>72</sup>. 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 and ocean acidity and temperature among many other variables. By linking these two models, the IGSM also allows for the development of emissions pathways consistent with different 21st century temperature outcomes.

### Monte Carlo simulation

Following earlier approaches<sup>33,34</sup> we employ Monte Carlo uncertainty analysis. The basic steps are: (1) identify uncertain input parameters and develop probability distributions for each, (2) sample from these distributions to construct multiple sets of parameter values, and (3) generate large ensembles of model runs using the sampled parameter values. The distribution of model outcomes from the ensemble of simulations for a particular scenario provides estimates of future states and their uncertainty, conditional on the model structure, the distributions of the uncertain input parameters, and the assumed scenario attributes. Figure 8 depicts this approach for representing uncertainty in a coupled human-Earth systems model (the MIT IGSM), creating probabilistic, internally consistent, integrated socio-economic and climate projections.

Probability distributions for socioeconomic input parameters<sup>19</sup> and for Earth system input parameters<sup>41,44,45</sup> were developed. Our focus on parametric uncertainty does not account for structural uncertainty in the models, such as equations defining objective functions, consumer preferences or the form of production functions. A summary of



**Fig. 8 | Approach for representing uncertainty in a coupled human-Earth systems model (The Massachusetts Institute of Technology (MIT) Integrated Global System Model (IGSM)).** Approach used to create probabilistic, internally consistent, integrated socio-economic and climate projections.



the probability distributions for all uncertain parameters, both socio-economic and Earth system, is provided in Supplementary Methods 1.

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 judgment (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, and enforced in the parameter samples, based on observed correlation where possible, but often based on expert judgment.

Uncertain Earth system parameters were estimated using an optimal fingerprint approach<sup>41,44,45</sup>. 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<sup>73</sup> used data only up to 1995. We also account for uncertainty in the carbon uptake by the ocean and terrestrial ecosystems<sup>72</sup>.

To reduce computational requirements when conducting Monte Carlo analysis with the relatively complex IGSM, we employ Latin Hypercube sampling (LHS)<sup>46,47</sup>. 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 input 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. Because our models are computationally expensive to run, 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<sup>34</sup>. The LHS takes in the correlation matrices that were developed for subsets of socio-economic parameters and captures the correlation among climate parameters by drawing from their joint distribution.

The same set of 400 samples is used for a reference scenario and a set of climate policy scenarios. 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 enable estimation of policy costs (the difference between simulated macroeconomic outcomes in a policy case and that in the reference case) for each ensemble member.

## Scenarios

Climate policy is treated as a choice variable (or deep uncertainty) in our framework, 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 implemented as a cap-and-trade policy fixing the emissions path over time. (See Supplementary Table 1). Morris et al.<sup>19</sup> explore the same set of scenarios (labeled by their median temperature outcomes), focusing on technology and socio-economic outcomes. The different scenarios are achieved by implementing different limits on emissions; all other

assumptions and sampled input values are the same across scenarios. 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<sup>48</sup> and those policies remain in place in all scenarios. 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<sup>74,75</sup>. For countries with absolute NDC targets (e.g. emission reductions relative to a historic year), we have implemented those as emissions caps that 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<sup>76</sup>.” 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<sup>77</sup>. We interpret the 1.5 °C aim as the median result, achieving it with a 50% probability. For both temperature-target scenarios, we assume all countries meet their NDCs by 2030, after which a global emissions price designed to achieve the long-term target 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% probability of remaining below 2 °C (Paris2C) above pre-industrial levels or a 50% probability of remaining below 1.5 °C (Paris1.5C) above pre-industrial levels. The resulting regional emissions trajectories are then implemented in all ensemble members as emissions caps with trading among sectors, regions and greenhouse gases to ensure that the temperature targets are met in all cases. The emissions caps are binding upper limits on emissions, and assure that the global emissions path determined under median values of socio-economic inputs are also met when those 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.

There are many alternative emissions trajectories that could also achieve the same outcomes (66% chance of 2 °C or 50% chance of 1.5 °C). For the particular pathways 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 Paris1.5 C 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 Paris1.5 C, the emissions path resulting from the global emissions price policy is directly implemented as an emissions cap for the ensemble.

In reality, countries may not meet their emissions targets with certainty. Nevertheless, we represent these emissions targets as being achieved with certainty. An interesting exercise could be to conduct an assessment asking experts for their judgment of the range of emissions paths that countries may achieve over the century. Such an approach would quantify the uncertainty in policy rather than treating it as a choice variable.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

### Data availability

Data from this study is available in a publicly available data repository: Morris, J., et al. Quantifying Both Socioeconomic and Climate Uncertainty in Coupled Human-Earth Systems Analysis [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.11622859><sup>78</sup>.

### Code availability

A publicly available version of the Economic Projection and Policy Analysis (EPPA) model is available at: <https://globalchange.mit.edu/research/research-tools/human-system-model/download>. The version of the model applied here includes an updated and expanded representation of technology options, as well as updates to read in samples from input files. The model is written in GAMS (General Algebraic Model System software, <https://www.gams.com>). The underlying base year model data is from the Global Trade Analysis Project (GTAP), Version 8 (<https://www.gtap.agecon.purdue.edu/databases/default.asp>). For the Monte Carlo Analysis, socioeconomic parameter samples are drawn from the distributions using @Risk software (<https://www.palisade.com/risk/>) and the ensembles of model runs are performed on the MIT computing cluster. A publicly available version of the MIT Earth System Model (MESM) is available at: <https://globalchange.mit.edu/media/mesm-software-license-form>.

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## Author contributions

J.R. and R.P. conceived the overall idea. J.M. and A.S. led the implementation of the idea. J.M. quantified socio-economic uncertainties, incorporated those uncertainties into the human system model, performed the human system model simulations and conducted the corresponding data analysis. A.L. and C.F. quantified the climate system uncertainties. A.S. incorporated the climate uncertainties into the Earth system model, performed the Earth system model simulations and conducted corresponding data analysis. J.M. and A.S. led the interpretation of results, with input from J.R., S.P., C.A.S., R.P. and H.J.J.M. created the figures for the manuscript and the data repository, and generated the first draft of the manuscript. J.R., A.S., S.P., C.A.S., R.P.

and H.J. provided edits to the manuscript, with J.M. and J.R. shaping the final version.

## Competing interests

The authors declare no competing interests.

## Additional information

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