TITLE: EQUITY MORE IMPORTANT IN SOCIAL COST OF METHANE THAN CLIMATE UNCERTAINTY

Authors: Frank C. Errickson[1,2], Klaus Keller[3,4], William D. Collins[5,6], Vivek Srikrishnan[3,7], David Anthoff [2*]

Affiliations: [1] School of Public and International Affairs, Princeton University, Princeton, NJ, USA. [2] Energy and Resources Group, University of California-Berkeley, Berkeley, CA, USA. [3] Earth and Environmental Systems Institute, The Pennsylvania State University, University Park, PA, USA. [4] Department of Geosciences, The Pennsylvania State University, University Park, PA, USA. [5] Lawrence Berkeley National Laboratory, Berkeley, CA, USA. [6] Department of Earth and Planetary Science, University of California-Berkeley, Berkeley, CA, USA. [7] Department of Biological & Environmental Engineering, Cornell University, Ithaca, NY, USA.

* Corresponding author: anthoff@berkeley.edu

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The social cost of methane (SC-CH4) measures the economic welfare loss caused by emitting one ton of methane into the atmosphere. This valuation may in turn be used in cost-benefit analyses or to inform an optimal taxation framework designed to reduce the impact of methane on climate[1-3]. Yet, current SC-CH4 estimates neglect key scientific findings and observational constraints. Here we estimate the SC-CH4 incorporating the recent 25% upward revision to methane radiative forcing calculations[4], combined with calibrated reduced-form global climate models and an ensemble of integrated assessment models (IAMs). Our multi-model mean estimate for the SC-CH4 is $933/t-CH4 ($471-1,570/t-CH4, 5-95% range) under the high emission Representative Concentration Pathway (RCP) 8.5, a 22% decrease compared to estimates based on the climate uncertainty framework recently used by the U.S. federal government under the Obama administration[5]. Our 95th percentile SC-CH4 estimate is 51% lower than the corresponding U.S. figure. Under the lower emissions in RCP2.6, our multi-model mean falls to $710/t-CH4 ($361-1,160/t-CH4, 5-95% range). Tightened equilibrium climate sensitivity estimates paired with the effect of previously neglected relationships between uncertain climate model parameters lower these estimates. Our SC-CH4 estimates are sensitive to model combinations, especially among IAMs. For example, within one IAM, different methane cycle sub-models can induce an approximate 20% variation in estimated SC-CH4. But switching IAMs can more than double the estimated SC-CH4. Extending our results to account for societal concerns about equity produces SC-CH4 estimates that differ by over an order of magnitude between low-and high-income regions. Our central equity-weighted estimate for the U.S. increases to $8,290/t-CH4 ($4,560-12,900/t-CH4, 5-95% range) while our estimate for sub-Saharan Africa decreases to $134/t-CH4 ($74-209/t-CH4, 5-95% range).

Economically efficient climate policy requires balancing the present costs of reducing methane emissions against future benefits from avoided climate impacts[3]. The SC-CH4 helps quantify this tradeoff by approximating the net present value of economic damages from emitting one ton of methane into the atmosphere. The few existing SC-CH4 estimates[6–10] influence a wide array of climate policy decision-making. The California Air Resources Board relied on the SC-CH4 for evaluating strategies to meet the greenhouse gas emission targets mandated by the California Global Warming Solutions Act of 2006[11]. At the federal level, the U.S. government uses the SC-CH4 in cost-benefit analyses and recently estimated that methane emission reductions from proposed oil and natural gas regulations could produce over $1 billion in climate benefits[12] (All comparisons in this paper with official U.S. estimates use the SC-CH4 figures that were developed and used by the Obama administration[5]. The Trump administration has since withdrawn these estimates and now uses a domestic measure of the SC-CH4[13]).

The SC-CH4's policy relevance creates a need for SC-CH4 estimates that carefully reflect our current understanding of the climate system and the corresponding decision-relevant uncertainties. While past SC-CH4 estimates[6–10] provided important initial insights into the societal harm caused by methane emissions, several major shortcomings make them an inadequate basis for further research and policy design. Specifically, past SC-CH4 values rely on underestimates of methane's radiative forcing[4] and are silent on the effect important parametric uncertainties and their potential interactions have on climate damage projections (Extended Data Table 1). Producing sound SC-CH4 estimates also requires climate models that enable a careful sampling of the parameter space and are sophisticated enough to replicate key behaviors simulated in comprehensive Earth System models. The climate models found in the cost-benefit integrated assessment models (IAMs) previously used for estimating the SC-CH4 do not meet this standard, contain well-known flaws[14,15], and have not been rigorously calibrated to observations. They may therefore produce biased SC-CH4 estimates inconsistent with the climate record.

Here, we use an ensemble of IAMs to provide improved, probabilistic SC-CH4 estimates that account for previously neglected climate uncertainties and the recent 25% upward revision to methane radiative forcing[4]. We create four simple, mechanistically motivated models of the coupled carbon, methane, and climate systems by pairing the Simple Non-Linear Earth System (SNEASY)[16] model to the original methane cycle components from: (i) the Finite Amplitude Impulse Response model (FAIR)[17], (ii) the Climate Framework for Uncertainty, Negotiation, and Distribution IAM (FUND)[18], (iii) the Hector climate model[19], and (iv) the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC)[20]. These models are hereafter referred to as *S-FAIR, S-FUND, S-Hector, and S-MAGICC*. Each model utilizes updated radiative forcing equations that account for new insights into methane's shortwave absorption[4] that previous studies ignored. We constrain the models to observations from 1850-2017 using a Bayesian framework. We then sample from the joint posterior parameter distribution, including the tails, which strongly influence projection uncertainties[21] (see Methods). While we consider a large number of uncertain parameters that may influence the SC-CH4, this list is by no means exhaustive (Extended Data Table 2). We further explore the SC-CH4's sensitivity to structural model uncertainties by coupling each calibrated climate model to the non-climate components of FUND and the Dynamic Integrated model of Climate and the Economy (DICE)[22], two leading cost-benefit IAMs previously used by the U.S. government to estimate the SC-CH4 (we refer to *FUND* as the IAM used for an SC-CH4 estimate, whereas *S-FUND* refers to the underlying simple climate model). For each climate model, we sample a parameter set from its joint posterior distribution and calculate the SC-CH4 for a one-ton methane pulse in 2020 under RCP8.5. We repeat this process 100,000 times per climate model-IAM combination to produce 800,000 unique SC-CH4 estimates.

<u>OBSERVATIONS CONSTRAIN SC-CH4 ESTIMATES</u>

We test our calibrated climate models through probabilistic hindcasts of surface temperature, ocean heat content, ocean carbon flux, as well as atmospheric carbon dioxide and methane concentrations (Fig.1, Extended Data Fig. 1). The hindcasts capture the spread of global surface temperature anomaly observations within their 95% predictive credible intervals reasonably well (Fig. 1a-d), a particularly relevant test because temperature increases drive DICE and FUND's climate damage projections. The atmospheric methane concentration hindcasts vary somewhat across models (Fig. 1e-h), with the simplest model, S-FUND, visibly exhibiting the least skill (Fig. 1f).

<u>PLACE FIGURE 1 HERE.</u>

We use the calibrated climate models to estimate a multi-model mean SC-CH4 of $933 ($471-1,570, 5-95% range) (2007 US dollars per metric ton CH_4, $/t-$CH_4$) under a constant 3% consumption discount rate (Fig. 2a). Both the 2007 price level and the 3% discount rate match the official U.S. figures to simplify comparisons. This represents a 22% decrease relative to the central U.S. estimate under the same discounting framework[5], though we note this U.S. value falls within our 95% SC-CH4 predictive credible interval. While a constant consumption discount rate facilitates a better comparison with official U.S. SC-CH4 estimates, it fails to account for linkages between economic growth and discounting[15]. In a sensitivity analysis, we recalculate the SC-CH4 under a standard Ramsey discounting framework[15] and obtain similar estimates (Extended Data Table 3). Our results also remain largely unchanged when considering a wider parameter space (Extended Data Fig. 4a).

Our SC-CH4 estimates are rather sensitive to forcing and emission scenario assumptions. Disregarding the recent upward revision to methane radiative forcing calculations[4] decreases our central SC-CH4 estimate by 16% (Fig. 2b, Extended Data Fig. 2). Switching from the RCP8.5 to RCP2.6 emissions scenario yields even larger changes in the SC-CH4. The lower background temperatures projected under RCP2.6 (Extended Data Fig. 3a-d) cause an additional methane emission pulse to be less damaging to society and decrease the multi-model mean SC-CH4 to $710/t-$CH_4$ ($361-1,160/t-$CH_4$, 5-95% range) (Extended Data Fig. 3e). This represents a 24% reduction relative to our RCP8.5 estimate, an effect comparable in magnitude to changes produced by some of the different discounting assumptions we consider (Extended Data Table 3).

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NON-LINEAR PARAMETER RELATIONSHIPS

As expected from physical reasoning and consistent with previous studies[16,23], several strong and non-linear relationships between the model parameters emerge from the calibrations. These relationships prove vital for the climate model's ability to produce results consistent with the observational record. For example, high equilibrium climate sensitivity (ECS) values are associated with increased aerosol cooling and more rapid ocean heat penetration that counteracts some additional surface warming that would otherwise occur (Fig. 3b, Extended Data Fig. 5a-c). Carbon cycle interactions further enrich this relationship. High ECS values are preferentially sampled alongside reductions in the sensitivity of terrestrial carbon pools to increasing temperatures.

Strong posterior relationships also arise between uncertain methane cycle parameters. In the S-MAGICC climate model, higher natural emission rates tend to partially offset cases where methane's time-varying atmospheric lifetime is initialized at a slightly lower value (Extended Data Fig. 4b). Perhaps surprisingly, we find little to no association between these uncertain methane cycle parameters and the SC-CH4 itself (Extended Data Fig. 4c). This stands in stark contrast to the ECS and aerosol cooling strength parameters (Fig. 3c, Extended Data Fig. 5d-f), suggesting the SC-CH4 responds more strongly to parametric uncertainties that directly influence temperature dynamics rather than methane cycle behaviors.

Neglecting these posterior relationships (see Methods) as done in previous studies[6–10] increases temperature projections (Fig. 3a, Extended Data Fig. 6) and SC-CH4 uncertainties (Fig. 2b, Extended Data Fig. 2). While our expected SC-CH4 estimates increase by 5-7% in this scenario, the standard deviation of a model's SC-CH4 estimates increase by 49-54%.

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Different treatments of these parametric climate uncertainties, with the ECS playing an important role, lower our multi-model mean SC-CH4 estimate. The U.S. SC-CH4 uncertainty framework[5] does not account for the types of parameter relationships described above and samples a pre-specified ECS distribution designed to be consistent with several broad statements about likely ECS ranges from the Intergovernmental Panel on Climate Change's Fourth Assessment Report[5,24]. Notably, the U.S. distribution yields increased probabilities of sampling high ECS values relative to our calibrated ECS distributions as well as recent ECS estimates that jointly account for information on climate system feedbacks, the paleoclimate record, and modern warming levels[25]. When we follow this aspect of the U.S uncertainty framework (see Methods), the climate models produce upwardly biased temperature hindcasts (Fig. 1a-d). This upwards bias is consistent with the expected effects of (i) the increased probability of sampling high ECS values from the U.S. distribution (Extended Data Fig. 7a) and (ii) neglecting the posterior parameter relationships that could partially offset the additional atmospheric warming from a high ECS. The association between the ECS and SC-CH4 also strengthens, with linear correlation coefficients equal to or exceeding 0.95 across all model combinations (Extended Data Fig. 7b-e). As a result, the multi-model mean SC-CH4 increases by 18% and more closely aligns with the official U.S. estimates (Fig. 2b, Extended Data Fig. 2). The 95th percentile SC-CH4, used in U.S. federal cost benefit analyses to represent high impact climate scenarios, exhibits considerable sensitivity to the upper ECS distribution tail and increases by 68% (Extended Data Table 3).

MODEL STRUCTURE AND SC-CH4 VARIATION

The results above weight each climate model equally and hence neglect key aspects of model structural uncertainty. Yet differences in hindcast skill suggest that weighting each model by its hindcast skill can further improve the quality of our results. To test this idea, we employ a Bayesian model averaging (BMA) framework[26] that weights our SC-CH4 estimates based on climate model posterior probabilities as a sensitivity analysis (see Methods). We find that the resulting BMA weights exhibit considerable variation across the four methane cycle models. More than 80% of the weight is given to S-MAGICC (0.88), followed by S-Hector (0.07), S-FAIR (0.04), and S-FUND (≈ 0.001). However, these BMA weights produce negligible changes to the SC-CH4 and increase the multi-model mean by 6%. This occurs, in part, because sampling different methane cycles has only a modest effect on the SC-CH4's expected value and distribution. For instance, switching the climate model from S-FUND (which consistently provides the lowest expected SC-CH4 estimates) to S-MAGICC (which often provides the highest) increases each IAM's expected SC-CH4 by roughly 22%. In contrast, switching IAMs from FUND to DICE for a given climate model increases the expected SC-CH4 by approximately 160%. This suggests non-climate differences between DICE and FUND produce greater variation in the SC-CH4 compared to the structural uncertainty of the underlying methane cycle models considered here, and that our model averaged results are relatively robust to the choice of methane cycle model weights. For simplicity, and to facilitate a direct comparison with EPA estimates, we hence report as the main results the average estimated derived from equally weighting the considered methane cycle models.

The differences separating DICE and FUND become starker when examining the time profile of their climate damage response to a one-ton methane emission pulse. Across multiple constant discount rates, DICE's projected annual marginal discounted damages peak between roughly $15-45 within a decade of the pulse and then slowly converge towards zero (Fig. 4b). In contrast, FUND often produces negative initial discounted damage estimates, projecting that society benefits from additional methane emissions in early periods (Fig. 4c). These benefits, which include increased agricultural productivity and avoided heating demand[27], partially explain FUND's consistently lower SC-CH4 estimates relative to DICE. However, in both IAMs the fading temperature pulse (Fig. 4a) paired with economic discounting pushes damage projections towards zero and leads to decreasing uncertainty over time. This effect becomes stronger under higher discount rates (Fig. 4b-c, inset).

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EQUITY-WEIGHTING

All of the results, thus far, use a constant consumption discount rate to facilitate comparison with official U.S. SC-CH4 estimates[5]. This approach is silent, however, on the question of equity. For example, a given consumption loss reduces a poor person's well-being more than a rich person's. Equity-weighting accounts for this effect by giving more weight to climate damages occurring in poorer regions. This approach is consistent with standard economic theory[28] as well as the call for common but differentiated responsibilities and respective capacities[29]. Equity-weighted social cost of carbon estimates receive considerable research attention and are currently used by the German government[30]. However, only a single published equity-weighted SC-CH4 estimate exists to our knowledge and this estimate does not account for the effects of climate model uncertainties[9].

Considering equity-weighting offers new perspectives, but also adds complexities. Our equity-weighting results use a social welfare function framework. The standard utilitarian social welfare function we employ captures that a dollar is “worth” more to a poor person than a rich person through the normative parameter of *inequality aversion* (η, see Methods). In an uncertain setting, η also represents a measure of risk aversion. To illustrate the importance of η for our equity-weighted SC-CH4 estimates, consider two individuals in a single time period with consumption levels of $1,000 and $10,000. When $\eta = 1.0$, a $1 decrease in consumption produces a welfare loss ten times greater for the poorer individual relative to the richer one. Increasing η to 1.5 causes the poorer individual’s welfare loss to be roughly thirty times greater. One can interpret the use of a constant consumption discount rate, as we do throughout this paper to match the U.S. SC-CH4 estimation approach, as equivalent to setting η to zero and implicitly adopting the ethical stance that $1 of forgone consumption has the same impact on well-being for rich and poor individuals alike (note though, that the specific pure rate of time preference rate we use is different from the constant consumption discount rate for our central results).

In the selected equity-weighting framework, we first aggregate climate damages from an additional ton of methane emissions as the global sum of discounted welfare losses across regions and over time. The resulting SC-CH4 estimate (measured in welfare terms) then needs to be monetized as a welfare equivalent consumption loss in the present in order to showcase the estimate in dollar units. Because socioeconomic inequities exist between regions and additional consumption has less “worth” as one gets richer, this conversion from welfare units to equivalent consumption losses results in different dollar amounts when expressed as a poor region’s versus a rich region’s consumption change. Therefore, equity-weighted SC-CH4 estimates are higher in monetary units when they are expressed as a consumption equivalent loss for a high-income region such as the United States, where an additional dollar of consumption has less influence on well-being, compared to a low-income region such as sub-Saharan Africa. The region used for this consumption equivalence computation is commonly referred to as the “normalization” region. Importantly, the choice of normalization region only affects the units (welfare equivalent consumption loss for a specific region) in which harms are presented. Different normalization regions do not alter the total estimated harm caused by an additional ton of methane, the same way as expressing distances in miles or kilometers does not change the length of a road trip (see

Methods). One important corollary is that the difference between our estimates that use different normalization regions is only driven by the ratio of per capita consumption levels in different normalization regions in the present (see Methods). For similar reasons, equity-weighting can yield different regional methane tax rates in an optimal taxation framework if consumption equalizing transfers between regions are either impossible or politically infeasible[31,32]. A complementary policy framework could also use equity-weighted SC-CH4 estimates to help identify an initial allocation of methane emissions permits accounting for equity, with permit trading between regions leading to additional economic benefits[32,33].

We generate equity weighted SC-CH4 distributions for FUND and report estimates for different choices of normalization region (DICE is a global model and can therefore not be used to compute equity-weighted results, see Methods). In our baseline estimates presented above that use a constant consumption discount rate of 3%, FUND produces an SC-CH4 of \$519/t-CH_4 (\$244-861/t-CH_4, 5-95% range). Under the full equity weighting framework, we find substantial SC-CH4 variation based on each region's socioeconomic status (Fig. 5). Due to its higher consumption levels, the United States' expected equity-weighted SC-CH4 is \$8,290/t-CH_4 (\$4,560-12,900/t-CH_4, 5-95% range) when η equals 1.0, nearly sixty times higher than sub-Saharan Africa's value of \$134/t-CH_4 (\$74-209/t-CH_4, 5-95% range) (Fig. 5c). However, the spread between these estimates increases non-linearly with η (Fig. 5a and b). Increasing η to 1.5 as done in the example above increases the United States' SC-CH4 to \$34,100/t-CH_4 (\$21,500-54,400/t-CH_4, 5-95% range), now over four hundred times higher than sub-Saharan Africa's \$70/t-CH_4 (\$45-112/t-CH_4, 5-95% range) estimate. We also present a sensitivity run for FUND where we remove equity weighting between regions but still retain the social welfare function approach described above for the intertemporal aggregation of damages (see Methods). This sensitivity run produces a global SC-CH4 estimate of \$658 (\$296-1,100/t-CH_4, 5-95% range) when η equals 1.0 (Fig. 5c). Comparing this sensitivity run with the equity weighted results isolates the effect of taking inequality between regions into account: without equity weighting, each region that is engaged in a cost-benefit analysis of its climate mitigation efforts would compare its mitigation costs to benefits that are computed from the uniform SC-CH4 estimate of \$658, whereas in the equity weighting case the mitigation cost in a specific region would be compared to benefits that are computed from the equity weighted SC-CH4 that is normalized to that specific region (see Methods). The net effect of this is that in an equity weighted cost benefit analysis mitigation costs are compared with higher (lower) benefit estimates in high (low) income regions relative to the non-equity weighted case, thus justifying higher mitigation expenditures in high income countries and lower mitigation expenditures in low income countries when an equity weighting framework is used.

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DISCUSSION AND CAVEATS

The large SC-CH4 variations caused by decisions on how to aggregate marginal damages (discounting and equity weighting), different forcing scenarios, and IAM choice suggest other non-climate factors can play a vital role in estimating the SC-CH4. For instance, climate impact projections strongly depend on IAM damage functions as well as the model's ability to capture society's future climate adaptation efforts. These model elements contain a number of uncertainties[15,27] that are not incorporated into our SC-CH4 estimates. While we account for some structural uncertainty about the climate damage function by using two different IAMs, it is important to note that DICE and FUND do not reflect the full range or capture the highest damage estimates found in the climate impacts literature[34]. We also do not consider potential interactions between an IAM's uncertain climate and economic parameters. Relatedly, the U.S. SC-CH4 incorporates estimates from the PAGE model, while ours do not. This may bias our results downward[27]; however our qualitative findings still hold when restricting the comparison to the U.S. results produced by DICE and FUND alone[5]. As FUND is generally producing lower damage estimates than DICE, our equity-weighted results may also be biased downwards. More generally, the SC-CH4 does not account for local mitigation co-benefits[35] as well as methane's direct effect on public health and agricultural productivity[36]. Both are important additional factors to consider when designing methane emission policies, but are conceptually distinct from the SC-CH4.

Our results have direct implications for policies targeting methane emissions. Most importantly, they show improved and carefully constrained climate models produce economically meaningful reductions in SC-CH4 estimates. This reduction persists despite the 25% upward revision to methane radiative forcing and is particularly evident in estimates from the SC-CH4's deeply uncertain but decision-relevant upper tail. Our equity-weighted estimates can yield even larger variations in the SC-CH4 between low- and high-income regions, but importantly depend on society's tolerance for inequality and risk. Extending our work to explore the joint relationship between climate and socioeconomic uncertainties as well as the complex interactions that arise when accounting for equity represents a promising and policy-relevant avenue for future research.

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Main Text Figure Legends

Fig. 1 | Probabilistic climate hindcast skills vary with model choice and treatment of parametric uncertainties. Hindcasts over the model calibration period (1850-2017) using the S-FAIR (purple), S-FUND (teal), S-Hector (red), and S-MAGICC (orange) climate models. **a-d,** The annual average global surface temperature anomaly relative to the 1861-1880 mean, with yellow circles representing the temperature observations used in the calibration. **e-h,** The annual average atmospheric methane concentration, with different yellow shapes identifying the Law Dome ice core (triangles) and globally averaged marine surface (circles) atmospheric methane concentration observations. In all panels, solid black center lines depict the mean response across 100,000 model runs, with colored regions spanning the 95% predictive credible interval. Gray shading in the temperature hindcasts shows the 95% predictive credible interval for an experiment that samples the ECS distribution used for U.S. SC-CH4 estimates while fixing other uncertain climate model parameters at their mean posterior values (see Methods).

Fig. 2 | SC-CH4 distribution estimates. a, Main SC-CH4 distribution estimates using each calibrated climate model for RCP8.5 under a constant 3% consumption discount rate. Different colors identify the four climate models. White shapes along the x-axis show the estimated mean for FUND (circle) and DICE (diamond) when pooling together estimates from the four climate models. **b**, Alternative SC-CH4 experiments for the S-MAGICC climate model using a constant 3% consumption discount rate under RCP8.5. Colors identify each SC-CH4 experiment, with our main specification using Bayesian calibration ("Main SC-CH4 estimate", red), outdated radiative forcing equations that disregard methane's shortwave absorption ("Outdated CH_4 radiative forcing", orange), neglecting posterior relationships and sampling each parameter independently ("Remove parameter relationships", green), and sampling the ECS distribution used for U.S. SC-CH4 estimates while fixing other uncertain climate model parameters at their mean posterior values ("U.S. Climate Sensitivity", blue). Colored shapes depict the estimated means for the different distributions. In both **a** and **b**, different distribution line types distinguish between the FUND (solid) and DICE (dashed) IAMs.

Fig. 3 | Non-linear climate parameter relationships constrain probabilistic temperature projections and SC-CH4 estimates. a, Modeled annual average global surface temperature anomalies relative to the 1861-1880 mean using the S-MAGICC climate model. Yellow circles represent observations and solid black center line depicts the mean response across 100,000 model runs. Colored regions outlined by dashed lines span the 95% predictive credible interval. The outer gray colored regions bound the 95% predictive credible intervals for model projections that remove parameter relationships by sampling each marginal posterior distribution independently. The inset figures depict estimated temperature distributions for 2050 and 2100 using the full set of model runs from the baseline (colored) and no parameter relationship (gray) scenarios. **b**, Posterior relationships between four uncertain climate parameters for the S-MAGICC climate model. Different sized circles correspond to different terrestrial carbon pool respiration-temperature sensitivity values (with higher values signaling increasing heterotrophic respiration of carbon dioxide with temperature). Each dot's color scales with the vertical rate of heat diffusion into the ocean. **c,** Posterior relationships between three of the parameters depicted in **b** with the SC-CH4 estimated using the S-MAGICC climate model for RCP8.5 under a constant 3% consumption discount rate. Different sized diamonds and circles identify respiration temperature sensitivity values for DICE and FUND. Each point's color scales with the aerosol radiative forcing factor (with higher values signaling stronger aerosol cooling). Both **b** and **c** depict 5,000 randomly selected posterior estimates, with loess-smoothed curves (white lines) helping illustrate the relationship between x and y-axis values.

Fig. 4 | Discounted climate damage impulse response behavior and uncertainties strongly differ between DICE and FUND. a, Temperature impulse response behavior for the S-

MAGICC climate model from a one-ton methane pulse in 2020. Solid black center line depicts mean response across 100,000 model runs and outer dashed black lines bound the 95% predictive credible intervals. Orange lines show 1,000 randomly sampled individual model runs. Colored circles identify the corresponding temperature distributions in the inset figure for the years 2030, 2040, 2050, and 2070 estimated from 100,000 model runs. **b**, Discounted climate damage impulse response behavior for DICE paired with the S-MAGICC climate model from a one-ton methane pulse in 2020. In each year, the predicted climate damages are discounted based on constant consumption discount rates of 2.5% (orange), 3% (red), 5% (blue), and 7% (green). For each discount rate, lines outlined in black show the mean model response while colored lines show 250 randomly sampled individual model runs. The inset figure shows discounted damage distributions estimated from 100,000 model runs under 2.5% and 5% constant discount rates for the years 2030, 2040, 2050, and 2070, with each year distinguished by a different line type. **c**, same as in **b** but depicting results for FUND.

Fig. 5 | Variations in equity-weighted SC-CH4 estimates and their uncertainties for different inequality aversion values. All estimates produced with the S-MAGICC climate model for RCP8.5 using a 1.0% pure rate of time preference. **a,** Equity-weighted SC-CH4 estimates for five FUND regions as the inequality aversion increases from 0 to 1.5 (higher values correspond to increasing preferences for equality in consumption). Different colors depict different regions, with the outer edges of each color representing the equity-weighted SC-CH4 95% predictive credible interval. Centered lines outlined in black show the expected equity-weighted SC-CH4. The dashed horizontal gray line bounds all estimates that fall below \$4000/t-CH_4. **b**, Zoomed-in view of the estimates in **a** falling below the \$4000 boundary. The dashed black line shows the mean SC-CH4 estimates for a sensitivity analysis that retains the welfare function approach but removes the influence of equity weighting by neglecting regional inequalities. **c**, Equity-weighted SC-CH4 distributions when inequality aversion equals 1.0. These distributions correspond to the vertical slice in **a** identified by the red arrow. Colored circles show the estimated means of the different distributions. To improve graph legibility, distributions for the sub-Saharan Africa and China + (China, Hong Kong, North Korea, Macau, and Mongolia) regions have been cropped. The dashed line distribution depicts SC-CH4 estimates for the sensitivity analysis that removes equity weighting.

Methods

Model coupling

We improve the representation of climate system dynamics in DICE[22] and FUND[18] by pairing each IAM to new models of the coupled carbon, methane, and global climate systems. We model the dynamics of the carbon cycle and climate with the Simple Non-Linear Earth System Model (SNEASY). SNEASY couples a simple representation of the climate system with a non-linear carbon cycle and has been thoroughly described elsewhere[16]. Since SNEASY does not contain an endogenous representation of the methane cycle, we couple it with the methane cycle components from four different models. We describe this procedure in greater detail below.

Briefly, SNEASY includes ocean and terrestrial carbon cycle models that respond to temperature changes through a feedback with the climate module[16,37]. The ocean carbon cycle consists of a four-layer diffusion model, with the top layer representing the atmosphere and mixed ocean surface. The terrestrial carbon cycle accounts for the leafy vegetation, living wood, detritus, and soil carbon sinks.

The climate component is based on the Diffusion Ocean Energy balance CLIMate model (DOECLIM)[38,39], a globally aggregated energy balance model that couples a zero-dimensional atmosphere to a one-dimensional diffusion model of the ocean. While DOECLIM distinguishes between land masses and the ocean, the low dimension is, of course a drastic approximation to the complex spatial patterns of climate change. The global mean surface temperature represents an area-weighted average of land and sea surface temperature anomalies resulting from an induced radiative forcing.

In the original version of SNEASY, radiative forcing from sources other than changing atmospheric carbon dioxide concentrations enter the model exogenously. We create four new versions of SNEASY that endogenously estimate changes in methane's atmospheric concentration and the resulting global surface temperature response by coupling SNEASY to the methane cycle components from: (i) the Finite Amplitude Impulse Response model (FAIR)[17], (ii) the FUND model[18], (iii) the Hector climate model[19], and (iv) the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC)[20]. We further update each model to use improved radiative forcing equations for carbon dioxide and methane that importantly account for the recent upward revision to direct methane radiative forcing estimates[4]. For methane's indirect effects on stratospheric water vapor and tropospheric ozone, we use each model's original radiative forcing equations. We also follow each model's original approach for quantifying the additional carbon dioxide produced by fossil fuel-based methane oxidation; S-FAIR and S-MAGICC account for this oxidation effect while S-FUND and S-Hector do not.

We make two additional model modifications. First, we convert MAGICC, which takes methane concentrations as an input before the year 2000 and then switches to methane emission inputs, to use methane emissions for all time periods. This allows us to use methane concentration data from before the year 2000 as an observational constraint. Second, the original FAIR model uses a fitted, time-varying natural methane emission scenario to ensure the model output matches historic atmospheric methane concentration values[17]. After 2005, the model switches to a constant natural methane emission rate for all subsequent years. We replace FAIR's fitted natural methane emissions scenario with a constant natural emission rate (following the approach adopted by Hector and MAGICC) to avoid artificially inflating the model's atmospheric methane concentration hindcast skill. For each model, we treat annual natural methane emission rates as an uncertain parameter. The calibration jointly samples values for these emission rates alongside the other uncertain methane cycle and climate parameters (Extended Data Table 2) to produce model output consistent with the set of observational constraints.

Calibration and forcing data

We use annual observational time series data of the climate system to calibrate each model over the period 1850-2017. Each dataset provides measurement error estimates that enter our statistical calibration framework (described below). The data include atmospheric carbon dioxide concentrations from Mauna Loa[40,41] and Law Dome ice cores[42], chlorofluorocarbon based estimates of oceanic carbon fluxes[43], the HadCRUT4 global temperature data set[44], and measurements of 0-3000 meter depth ocean heat uptake[45]. Although SNEASY has a 4000-meter ocean, we assume minimal heat exchange occurs below 3000 meters during the calibration time horizon[46]. The calibration also utilizes atmospheric methane concentrations from globally averaged marine surface data[47] and Law Dome ice cores[48]. Following past work[48], we calculate the globally averaged atmospheric methane concentration from the ice core data as the Law Dome measurement plus 37% of the annual interpolar methane concentration difference.

We run the models using greenhouse gas emission and radiative forcing values from RCP8.5[49,50], a no-policy scenario that closely tracks current carbon dioxide emission levels[51,52], but helps highlight differences in methane cycle model behavior by providing large forcing and emission signals in future years. In a sensitivity test, we repeat our analysis using the RCP2.6 scenario. Each model exogenously accounts for radiative forcing effects from solar and volcanic activity, direct and indirect effects of aerosols, land use albedo changes, stratospheric ozone, black carbon on snow, and anthropogenic greenhouse gases other than carbon dioxide or methane. The greenhouse gas forcing values include fluorinated gases regulated by the Kyoto protocol in addition to all gases controlled under the Montreal Protocol.

Unlike the other models in this study, SNEASY-F (SNEASY + the FUND methane cycle) approximates methane's indirect radiative forcing from stratospheric water vapor and tropospheric ozone as 40% of methane's direct radiative forcing [5,18]. However, SNEASY-F does not endogenously calculate total tropospheric ozone radiative forcing. Simply running SNEASY-F with or without the RCP8.5 tropospheric ozone radiative forcing values would therefore produce biased parameter estimates and model projections. To address this issue, we use the FUND methane cycle model to derive an exogenous, RCP8.5 consistent radiative forcing scenario for tropospheric ozone's non-methane component.

Step (1): Calculate the tropospheric methane lifetime that minimizes the root-mean-square error (RMSE) between modeled atmospheric methane concentrations and RCP8.5 concentrations over the calibration period 1850-2017.

Step (2): Use the RMSE minimizing methane lifetime and RCP8.5 methane emission values to project atmospheric methane concentrations out to 2300.

Step (3): FUND calculates methane's indirect radiative forcing due to tropospheric ozone as 25% of methane's direct radiative forcing[5,53]. Using this factor and the concentration time series from Step (*2*), calculate FUND's predicted methane contribution to tropospheric ozone radiative forcing.

Step (4): Subtract FUND's predicted methane contribution from the RCP8.5 total tropospheric ozone radiative forcing time series. This difference serves as an exogenous input to SNEASY-F for the non-methane component of tropospheric ozone radiative forcing.

Bayesian model calibration

To derive statistically sound parameter estimates that provide results consistent with the historic climate record, we calibrate each model using a Bayesian framework. The joint posterior distribution $p(\theta \vee y)$ for climate model *j* represents the probability of observing the uncertain parameters θ after accounting for information contained in the climate observations y and comes from Bayes' Theorem:

$$p(\theta_j \vee y) = \frac{p(\theta_j)\, L(y \vee \theta_j)}{p(y)} \qquad (1)$$

Here, the prior distribution $p(\theta_j)$ expresses prior knowledge about the uncertain parameters and the likelihood function $L(y \vee \theta_j)$ provides the likelihood of observing the data given model *j*'s parameters. The denominator $p(y)$ represents a normalizing constant that often requires numerical approximation, making it difficult to perform Bayesian inference on even relatively simple climate models. We overcome this issue by using the robust adaptive Markov chain Monte Carlo (MCMC) algorithm within our Bayesian framework[54–57]. This approach allows us to sample $p(\theta_j \vee y)$ by calculating equation (1) up to proportionality, making it a computationally tractable model calibration approach[56–58].

We adopt physically-informed truncated uniform prior distributions for all uncertain model parameters except for the equilibrium climate sensitivity *ECS*, the vertical diffusivity of heat into the ocean K_v, a multiplicative scaling factor on aerosol radiative forcing α, and the initial global surface temperature anomaly T_0 (Extended Data Table 2). For these parameters, we follow previous work and adopt subjective prior distributions[16]. The *ECS* prior uses a truncated Cauchy distribution to account for paleoclimate information not utilized in the calibration while K_v uses a log-normal prior to reflect data derived from biogeochemical tracers[16]. We use a triangular distribution for α to approximate IPCC estimates on the total radiative forcing effects of aerosols. Finally, we use a standard normal distribution centered on zero to describe uncertainty about T_0. The prior distributions for all uncertain parameters are assumed to be independent, with their product giving the joint prior distribution from equation (1).

We calculate the likelihood function from equation (1) in terms of the residuals between the observed and modeled climate. Past work shows that assuming too simple of an error structure in the statistical model fitting framework can produce biased parameter estimates and overconfident model projections, particularly for low-probability tail events[21,37,59]. We address this issue by approximating the residuals using autoregressive process models that also account for time-varying observation errors contained in the data[21]. For time series *n* of observed data *y* at time *t*, model *j*'s residual ε_{jnt} represents the difference between the model output $f(\theta)_{jnt}$ and observations:

$$f(\theta)_{jnt} - y_{nt} = \varepsilon_{jnt} \quad (2)$$

The data-model residuals in equation (2) consist of two distinct components:

$$\varepsilon_{jnt} = e_{jnt} + \omega_{nt} \quad (3)$$

where the autoregressive model error e_{jnt} represents the potential residual autocorrelation and ω_{nt} represents time-varying observation error. We assume the observation errors come from a mean-zero normal distribution with a time-varying variance $\sigma^2_{nt\ obs}$ given by measurement error estimates provided with each calibration dataset $\omega_{nt} \sim \mathcal{N}\left(0, \sigma^2_{nt\ obs}\right)$.

The global mean surface temperature anomaly and oceanic heat content time series both contain annually consecutive observations. We hence model the corresponding residuals using a stationary first order autoregressive process, or AR(1), model. In this framework, the value of e_{jnt} depends linearly on the previous residual through a first-order autocorrelation coefficient ρ_{jn} that varies across datasets but remains constant over time:

$$e_{jnt} = \rho_{jn} \times e_{jn(t-1)} + \delta_{jnt} \tag{4}$$

Equation (4) also contains an independent and identically distributed (i.i.d.) stochastic error term $\delta_{jnt} \sim i.i.d.\ \mathcal{N}\left(0, \sigma^2_{jn\ AR1}\right)$, with $\sigma^2_{jn\ AR1}$ the AR(1) innovation variance for data set n. δ_{jnt} captures remaining structural model errors and natural climate variability unable to be resolved by the simplified climate models used in this study. We treat ρ_{jn} and $\sigma^2_{jn\ AR1}$ as uncertain statistical process parameters and estimate them during model calibration.

The covariance matrix Σ_{jn} for the global mean surface temperature anomaly and oceanic heat content time series represents the sum of the AR(1) process and time-varying observation error variances:

$$\Sigma_{jn} = \frac{\sigma^2_{jn AR1}}{1-\rho^2_{jn}} \begin{pmatrix} 1 & \rho_{jn} & \rho^2_{jn} & \cdots & \rho^{k-1}_{jn} \\ \rho_{jn} & 1 & \rho_{jn} & \cdots & \rho^{k-2}_{jn} \\ \rho^2_{jn} & \rho_{jn} & 1 & \cdots & \rho^{k-3}_{jn} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{k-1}_{jn} & \rho^{k-2}_{jn} & \rho^{k-3}_{jn} & \cdots & 1 \end{pmatrix} + \begin{pmatrix} \sigma^2_{n1obs} & 0 & 0 & \cdots & 0 \\ 0 & \sigma^2_{n2obs} & 0 & \cdots & 0 \\ 0 & 0 & \sigma^2_{n3obs} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma^2_{nk\,obs} \end{pmatrix} \tag{5}$$

The atmospheric carbon dioxide and methane concentration time series both contain a combination of irregularly spaced ice core and more recent instrumental observations. We model the corresponding residuals with a stationary first-order continuous time autoregressive, or CAR(1), model. A detailed description of this approach can be found in ref. [60]. The CAR(1) model contains a continuous time white noise process with variance $\sigma^2_{jn-CAR1}$ and a correlation memory process that decays exponentially with time and is characterized by the term $\alpha 0_{jn}$. We treat $\sigma^2_{jn-CAR1}$ and $\alpha 0_{jn}$ as additional uncertain parameters and estimate them during model calibration.

The covariance matrix for the atmospheric carbon dioxide and methane concentration time series then represents the sum of the CAR(1) process and time-varying observation error variances[60]:

$$\Sigma_{jn} = \frac{\sigma^2_{jn-CAR1}}{2\alpha_{jn}} \begin{pmatrix} 1 & e^{-\alpha 0_{jn}(|t_1-t_2|)} & \cdots & e^{-\alpha 0_{jn}(|t_1-t_k|)} \\ e^{-\alpha 0_{jn}(|t_2-t_1|)} & 1 & \cdots & e^{-\alpha 0_{jn}(|t_2-t_k|)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-\alpha 0_{jn}(|t_n-t_1|)} & e^{-\alpha 0_{jn}(|t_n-t_2|)} & \cdots & 1 \end{pmatrix} + \begin{pmatrix} \sigma^2_{n1obs} & 0 & \cdots & 0 \\ 0 & \sigma^2_{n2obs} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2_{nkobs} \end{pmatrix} \quad (6)$$

where *e* is the natural exponential function, and $|t_n - t_k|$ describes the time interval between potentially irregularly spaced observations for years *n* and *k*. For this analysis, we compare each Law Dome atmospheric carbon dioxide and methane concentration observation with the eight-year average of modeled concentrations, centered on each ice core observation's corresponding year[16].

For the observational datasets mentioned above, we use a likelihood function that assumes the full residual time series $\vec{\varepsilon}_{jn}$comes from a k_n-dimensional multivariate normal distribution[21] characterized by the appropriate covariance matrix $\vec{\varepsilon}_{jn} \quad \mathcal{N}_k(0, \Sigma_{jn})$. We write the likelihood function[21] for dataset *n* as:

$$L(\vec{y}_n \vee \theta_j, \Sigma_{jn}) = \left(\frac{1}{\sqrt{2\pi}}\right)^{k_n} |\Sigma_{jn}|^{\frac{-1}{2}} \exp\left[\frac{-1}{2}\left(\vec{y}_n - \vec{f}(\theta)_{jn}\right)^{\top} \Sigma^{-1}_{jn}\left(\vec{y}_n - \vec{f}(\theta)_{jn}\right)\right] \quad (7)$$

The ocean carbon flux dataset lacks annually consecutive observations. We therefore neglect any potential autocorrelation and apply a likelihood function that assumes normally distributed i.i.d. residuals. We hold the ocean carbon flux standard deviation constant at the reported observational error[43] of 0.4 Pg C/yr.

Under the simplifying assumption that residuals across data sets are independent, the product of the individual likelihoods gives the total likelihood of the observational climate data.

For each version of SNEASY, we set the MCMC target distribution to the numerator of equation (1) (i.e. the product of the prior and likelihood) and produce a Markov chain that constitutes a representative sample from the joint posterior parameter distribution. We check for convergence to the target distribution using graphical diagnostics and potential scale reduction factor calculations[61]. Each chain contains six million parameter samples and we discard the first one million sampled parameters for the burn-in period. We then thin the remaining chain down by selecting a subset of 100,000 parameter samples at equally spaced intervals.

Estimating the social cost of methane (SC-CH4)

For each posterior parameter sample and corresponding IAM combination, we produce a unique SC-CH4 estimate following a four-step process. In the first step, we select a single posterior parameter sample for a given model and calculate two climate trajectories out to 2300; (1) a baseline model run following the RCP8.5 scenario and (2) a pulse run that adds one extra ton of methane emissions in 2020 but is otherwise identical to the baseline run. The resulting climate projections contain superimposed noise to account for process and observation uncertainty[21]. For posterior parameter sample i and climate model j, we simulate this noise term for the nth calibration data set variable (e.g. annual global surface temperature anomalies) by sampling from a mean-zero multivariate distribution characterized by the covariance matrices from equations (5) and (6). We assume years occurring outside the periods with data coverage have observation measurement errors equivalent to the average of the ten nearest observation measurement errors in time.

In the second step, we pair the uncertain climate projections with an IAM to calculate climate damage estimates. This produces two damage trajectories, a baseline trajectory and one that accounts for the additional impacts caused by the one-ton methane pulse in 2020.

In the third step, we use IAM k to calculate annual marginal climate damages MD_{kjit} as the difference in damages D_{kjit} between the baseline and methane pulse trajectories:

$$MD_{kjit} = D_{kjit(pulse)} - D_{kjit(baseline)} \quad (8)$$

Because the DICE model runs on 5-year timesteps[22], we linearly interpolate the DICE damage estimates in equation (8) to produce annual values.

In the fourth and final step, we calculate the SC-CH4 for a given posterior parameter sample and model combination as the discounted sum of marginal damages across r regions and over time:

$$SC\,CH\,4_{kji} = \sum_{t=0}^{T} \sum_{r=1}^{R} MD_{kjitr} \times \frac{1}{(1+\Phi)^t} \quad (9)$$

where Φ represents a constant consumption discount rate. We set Φ to 3% in our main results to compare with the central estimates currently used by the U.S. federal government, which are based on a constant 3% rate[5]. We further align our results with reported U.S. SC-CH4 values by expressing our estimates in 2007 U.S. dollars using conversion factors derived from U.S. Bureau of Labor Statistics inflation data[62].

We repeat this entire process for each posterior parameter sample and corresponding climate-IAM model pair. With two IAMs, four climate models, and 100,000 posterior parameter samples per climate model, this yields 800,000 unique SC-CH4 estimates (Fig. 2a).

Bayesian model averaging

To address uncertainty in climate model selection, we employ a Bayesian model averaging (BMA) approach that places greater weight on models better able to produce results consistent with past observations[26,63]. More formally, the SC-CH4 estimates corresponding to the jth climate model M_j are now weighted based on that model's posterior probability:

$$BMA_j = p(M_j \vee y) = \frac{p(y \vee M_j)\, p(M_j)}{\sum_{q=1}^{4} p(y \vee M_q)\, p(M_q)} \quad (10)$$

Where BMA_j represents the BMA weight for climate model j and we assume each candidate climate model's structure has an equal prior probability $\left(p(M_j) = p(M_l)\, for\ all\ j, l\right)$. Making model dependence explicit, the probabilities $p(y \vee M_j)$ are given by:

$$p(y \vee M_j) = \int_{\theta_j} p(y \vee \theta_j, M_j)\, p(\theta_j)\, d\theta_j \quad (11)$$

where θ_j corresponds to the calibrated parameters for climate model j. We follow previous work[26,64] by approximating equation (11) using bridge sampling and the posterior results obtained during model calibration with MCMC. The multi-model BMA-weighted SC-CH4 estimate can then be calculated as:

$$SC\,CH\,4_{BMA} = \sum_{j=1}^{4} SC\,\acute{C}H\,4_j \times BMA_j \quad (12)$$

where $SC\,\acute{C}H\,4_j$ represents the SC-CH4 averaged across DICE and FUND using climate model j.

Alternative SC-CH4 estimates

We provide four alternative SC-CH4 estimates to explore how our results change under different model structures and treatments of parametric uncertainties. We discard a small subset (< 0.3%) of parameter samples in these sensitivity analyses that produce model errors.

(1) Using outdated methane radiative forcing equations. We recalculate the SC-CH4 for each climate model-IAM pair using the original methane radiative forcing equations found in each methane cycle's parent model (Fig. 2b, Extended Data Fig.2). For FAIR, which provides the option to run the model under a variety of forcing assumptions, we select the older radiative forcing equations that do not account for methane's shortwave absorption[17,65]. Each SC-CH4 estimate therefore comes from a climate model that neglects the recent 25% upward revision to methane radiative forcing[4].

(2) Removing calibrated climate parameter relationships. Several posterior relationships between the uncertain parameters emerge during model calibration. These relationships act as an important constraint on model behavior (Fig. 3b and c, Extended Data Fig. 5), climate projection uncertainty (Fig. 3a, Extended Data Fig. 6), and the resulting SC-CH4 distributions (Fig. 2b, Extended Data Fig.2). For this analysis, we recalculate the SC-CH4 and remove these posterior relationships by assuming the calibrated climate and statistical process parameters come from independent distributions. We then sample from each marginal posterior distribution without replacement to produce new SC-CH4 estimates.

(3) Sampling equilibrium climate sensitivity only. Selecting an appropriate ECS value represents a persistent source of uncertainty for the simplified climate models found in IAMs[14,66,67]. Federal U.S. SC-CH4 estimates represent this uncertainty by sampling an ECS distribution parameterized to match several broad IPCC probability statements about the ECS[5,24]. We replicate this estimation strategy within our framework by fixing each uncertain parameter to its mean posterior value and sampling the ECS distribution used for U.S. SC-CH4 estimates[24,68] (Extended Data Fig. 7a). We calculate a new SC-CH4 value (Fig. 2b, Extended Data Fig.2) for each ECS value l sampled from:

$$ECS_l = \frac{1.2}{1-f} \tag{13}$$

where f comes from a normal distribution $f \quad \mathcal{N}(0.62, 0.034)$ truncated between -0.2 and 0.88 to capture uncertainty in climate system feedbacks[8].

(4) Wider prior parameter distributions. Using uniform or truncated prior distributions in the model calibration precludes sampling parameter values beyond their distribution bounds. We carry out a sensitivity analysis using wider prior distributions that allows the MCMC algorithm to explore a much larger parameter space (Extended Data Table 2). Based on these wider prior distributions, we recalibrate each of the four climate models to obtain new posterior parameter samples and then produce updated SC-CH4 estimates for each climate model – IAM pair (Extended Data Fig. 4a).

<u>Equity-weighting</u>

As discussed above, the SC-CH4 calculated from equation (9) uses a constant consumption discount rate to facilitate comparison with official U.S. SC-CH4 values[5]. This approach neglects the concept that an additional dollar of consumption more strongly affects the welfare of a low-consumption individual than a high-consumption individual. To address this concern, we use the FUND model to produce equity-weighted SC-CH4 estimates that also incorporate preferences on risk aversion[28]. We produce a new point estimate for each posterior parameter sample to derive equity-weighted SC-CH4 distributions. Under this framework, the equity-weighted SC-CH4 for climate model j and posterior parameter sample i is given by:

$$Equity\,SC\,CH\,4_{jix} = \underbrace{\left(\frac{1}{c_{ji0x}}\right)^{-\eta}}_{\substack{\text{conversion from}\\ \text{welfare to equiv.}\\ \text{consumption units}\\ \text{in the normalization region}}} \sum_{t=0}^{T} \underbrace{(1+\rho)^{-t}}_{\substack{\text{pure time}\\ \text{discount factor}}} \sum_{r=1}^{R} \underbrace{\left(\frac{1}{c_{jitr}}\right)^{\eta}}_{\substack{\text{conversion from}\\ \text{damage to}\\ \text{welfare units}}} MD_{jitr} \quad (14)$$

where η represents inequality aversion, ρ is the pure rate of time preference, MD_{jitr} represents marginal damages for region r in year t as described in equation (9), c gives regional per capita consumption and the x subscript identifies the normalization region used. Some simple algebraic manipulations of equation (14) allow one to rewrite the equation as

$$Equity\,SC\,CH\,4_{jix}=\underbrace{\sum_{r=1}^{R}\left(\frac{c_{ji0r}}{c_{ji0x}}\right)^{-\eta}}_{\substack{\text{equity}\\ \text{weight}}}\underbrace{\sum_{t=0}^{T}\left(\frac{c_{jitr}}{c_{ji0r}}\right)^{-\eta}(1+\rho)^{-t}}_{\substack{\text{regional Ramsey}\\ \text{discount factor}}}MD_{jitr} \qquad (14b)$$

This form highlights that the equity weighting procedure can also be described as first computing the net present value of marginal damages per region using a region-specific Ramsey discount factor, and then aggregating across regions using regional equity weights.

The x subscript identifies the normalization region used in the equity-weight term $\left(\frac{c_{ji0r}}{c_{ji0x}}\right)^{-\eta}$ to normalize the SC-CH4 into a welfare-equivalent loss of consumption for that specific region. The equity-weighted SC-CH4 therefore varies with x and depends heavily on the normalization region's consumption level in the present. Note that the normalization region in equation (14b) only appears in the denominator of the first fraction, in the term c_{ji0x}. This term represents the per capita consumption of the normalization region in the present. In this framework, the differences between different normalization regions only depend on differences in per capita consumption levels between regions in the present. The discount factor in equation (14b) depends on regional per capita growth, and thus regions with faster growth discount the future more strongly in this framework. At the same time, damages in poor regions receive more weight via the equity weight in equation (14b). The combined discount factor and equity weight consistently weighs impacts based on the relative position of the per capita consumption level of the affected population and any time discounting[28].

The underlying social welfare function from which equation (14) derives is a standard utilitarian social welfare function:

$$SWF=\sum_{t=0}^{T}\sum_{r}^{R}P_{tr}\,U(c_{tr})\left(\frac{1}{1+\rho}\right)^{t} \qquad (15)$$

We omitted the climate model and posterior parameter sample index for clarity. We use:

$$U(c)=\begin{cases}\log c & \text{iff } \eta=1\\ \dfrac{c^{1-\eta}}{1-\eta} & \text{iff } n\neq 1\end{cases} \quad (16)$$

as the utility function, a standard choice in the literature. The details of the derivation of equation (16) can be found in ref.[28].

For our main results, we set the parameters in equation (14) to values commonly found in the climate economics literature[28], namely η = 1.0 and ρ = 1.0% (Fig. 2c). In a sensitivity test, we also provide results across a range of η values (Extended Data Fig. 9). Note that our results do not account for income inequality or income-dependent vulnerability to climate impacts at the sub-regional level, which could potentially further increase the spread in equity-weighted SC-CH4 estimates between low- and high-consumption regions[69]. We report SC-CH4 estimates for several normalization regions. Our choice of normalization regions is designed to illustrate the effect for a sample of key regions by spanning a range of high- to low-income regions. How one should choose a particular normalization region in a cost benefit analysis is extensively discussed in refs.[28,70]. We here highlight some of the major results from this literature and refer the reader to the underlying equity weighting literature for the derivations of these results. In equity weighted cost-benefit applications, the choice of normalization region will not change whether a policy passes a cost-benefit test, as long as *all* costs and benefits are computed using the same equity weighting scheme and the same normalization region. To stay with the analogy from the main text: as long as one is careful to not mix units, one will get the same substantive results in distance computations, regardless of whether one expresses things in kilometers or miles. Similarly, the substantial conclusions from an equity weighted cost-benefit analysis do not change with the choice of normalization region, as long as one uses a consistent normalization region throughout the cost-benefit analysis[28]. In practice, particular normalization choices can simplify comparison with mitigation costs, though. For example, if a region wants to compare mitigation costs that are born solely by that region with the benefits of these emission reductions, then choosing that same region as the normalization region can greatly simplify such a comparison. The equity weight for the mitigation costs that accrue in this region will be unity in this case, which effectively means that the mitigation cost estimates can be directly compared to the equity weighted SC-CH4 estimates, without further conversions of the mitigation costs. To return one final time to the distance analogy: if one has a set of existing distance measures all in miles, it is easier to compare a new distance estimate to these if it is also in miles, rather than in kilometers.

We also provide an additional sensitivity analysis that uses the welfare function approach described above, but does not account for inequality in consumption between regions in the welfare calculation. This allows us to isolate the effect equity weighting has on the SC-CH4. In this framework, we estimate the SC-CH4 as:

$$SC\,CH\,4_{ji} = \sum_{t=0}^{T} \sum_{r=1}^{R} \left(\frac{C_{jit}}{C_{ji0}} \right)^{-\eta} (1+\rho)^{-t} MD_{jitr} \quad (17)$$

Here, C now represents global average per capita consumption levels at time t. To align these results with our equity weighted SC-CH4 estimates, we use the same value for ρ and provide estimates across a range of values for η. Note that because this framework no longer requires a normalization region, it will produce a single SC-CH4 estimate that does not vary across regions.

Uncertainty reporting

The primary objects of interest are the posterior distributions of key model parameters and the predictive distributions for quantities like the SC-CH4, the latter being the decision relevant uncertainties. When we report uncertainties in this manuscript, we generally attempt to characterize the shape of these distributions. For example, when we report credible intervals for key results, we are reporting the 5% and 95% percentile of these distributions. For reported multi-model results, we assign each model an equal weighting and average across the individual model estimates. In addition, percent ranges in the main text correspond to the spread of percentage changes in the expected SC-CH4 across all individual climate model-IAM pairings. Percent values are always relative to a model's baseline expected SC-CH4 estimate (RCP8.5 under a constant 3% consumption discount rate). We report our SC-CH4 results to three significant figures.

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Author Contributions

All authors designed the study. F.C.E. and D.A. led the computer modeling. All authors interpreted results and wrote the manuscript.

Competing Interests

The authors are not aware of competing interests.

Data availability

The replication code for this paper is available at https://doi.org/10.5281/zenodo.4541874, including instructions on how to rerun the entire analysis for this paper. The exact model versions used in this paper are MimiFAIR.jl v1.0.0 (https://doi.org/10.5281/zenodo.4321934), MimiSNEASY.jl v1.0.0 (https://doi.org/10.5281/zenodo.4321933), MimiMAGICC.jl v1.0.0 (https://doi.org/10.5281/zenodo.4321929), MimiHector.jl v1.0.0 (https://doi.org/10.5281/zenodo.4321932), MimiDICE2013.jl v1.0.1 (https://doi.org/10.5281/zenodo.4444147) and MimiFUND.jl v3.12.0 (https://doi.org/10.5281/zenodo.3986017). The code uses the Mimi.jl v1.1.1 framework (https://doi.org/10.5281/zenodo.4321856).

Extended Data Figure Legends

Extended Data Fig. 1 | Additional probabilistic climate hindcasts. Hindcasts over the model calibration period (1850-2017) using the S-FAIR (purple), S-FUND (teal), S-Hector (red), and S-MAGICC (orange) climate models. **a-d,** The annual atmospheric carbon dioxide concentration, with different shapes identifying the Law Dome ice core (triangles) and Mauna Loa (circles) calibration data. **e-h**, Annual ocean carbon flux. **i-l**, Global ocean heat content. In all panels, yellow shapes represent observations. Solid black center line depicts the mean response across 100,000 model runs, with colored regions spanning the 95% predictive credible interval.

Extended Data Fig. 2 | Additional SC-CH4 estimates under different model structures and treatments of parametric uncertainty. a, Distributions from the S-FAIR climate model for SC-CH4 experiment using a constant 3% consumption discount rate under RCP8.5. Different distribution line types identify the FUND (solid) and DICE (dashed) IAMs, with colored shapes along the x-axis marking the estimated means of the different distributions. Colors identify each SC-CH4 experiment, with our main specification using Bayesian calibration ("Main SC-CH4 estimate", red), outdated radiative forcing equations that disregard methane's shortwave absorption ("Outdated CH_4 radiative forcing", orange), neglecting posterior relationships and sampling each parameter independently ("Remove parameter relationships", green), and sampling the ECS distribution used for U.S. SC-CH4 estimates while fixing other uncertain climate model parameters at their mean posterior values ("U.S. climate sensitivity", blue). **b**, same as **a** but for the S-FUND climate model. **c**, same as **a** but for the S-Hector climate model.

Extended Data Fig. 3 | Using the RCP2.6 scenario keeps expected temperature projections below 2 °C and reduces SC-CH4 estimates relative to RCP8.5. a-d, Modeled annual average global surface temperature anomalies relative to the 1861-1880 mean under RCP2.6. Red dashed vertical lines identify the end of the calibration period (1850-2017). Yellow circles represent temperature observations and solid black center line depicts the mean response across 100,000 model runs. Colored regions span the 95% predictive credible intervals and horizontal gray lines identify the UN Paris Agreement's 1.5 °C and 2 °C global temperature targets. **e**, SC-CH4 distributions for FUND (solid line) and DICE (dashed line) using a constant 3% consumption discount rate under RCP2.6. White circles and diamonds show FUND and DICE's expected SC-CH4 for the two RCP scenarios after pooling together results from the four climate models. The percentage value identifies the percent change in each IAM's expected SC-CH4 that occurs when switching from RCP8.5 to RCP2.6, with the arrow identifying the direction of the change. In all panels, different colors identify the S-FAIR (purple), S-FUND (teal), S-Hector (red), and S-MAGICC (orange) models.

Extended Data Fig. 4 | Robustness of SC-CH4 distributions to wider prior assumptions, and posterior methane cycle parameter relationships. a, SC-CH4 distributions for FUND (solid line) and DICE (dashed line) depicting the main results (red) and a sensitivity analysis that uses wider prior parameter distributions during the model calibrations (blue). The SC-CH4 distributions correspond to a constant 3% consumption discount rate under RCP8.5 and pool each IAM's SC-CH4 estimates across the four climate models. Colored circles show the estimated multi-model mean SC-CH4 for the two scenarios. **b**, Posterior parameter relationship between natural methane emission rates and the initial value for methane's time-varying tropospheric lifetime in the S-MAGICC climate model. **c**, Posterior relationships between the uncertain methane cycle parameters depicted in **b** with S-MAGICC's estimated SC-CH4 for RCP8.5 under a constant 3% consumption discount rate. Different sized diamonds and circles identify methane's initial tropospheric lifetime for DICE (blue) and FUND (red). Both **b** and **c** depict 5,000 randomly selected posterior estimates, with loess-smoothed curves (white lines) helping illustrate the relationship between x and y-axis values.

Extended Data Fig. 5 | Additional models showing non-linear climate parameter relationships constrain SC-CH4 estimates. Parameter and SC-CH4 relationships for the S-FAIR (top row), S-FUND (middle row), and S-Hector (bottom row) climate models. **a-c,** Posterior relationships between four uncertain climate parameters. Different sized circles correspond to different terrestrial carbon pool respiration-temperature sensitivity values (with higher values signaling increasing heterotrophic respiration of carbon dioxide with temperature). Each dot's color scales with the vertical rate of heat diffusion into the ocean. **d-f,** Posterior relationships between three of the uncertain climate parameters depicted in **a-c** with the SC-CH4 estimated for RCP8.5 under a constant 3% consumption discount rate. Different sized diamonds and circles identify respiration temperature sensitivity values for DICE and FUND. Each point's color scales with the aerosol radiative forcing factor (with higher values signaling stronger aerosol cooling). Each panel depicts 5,000 randomly selected posterior estimates, with loess-smoothed curves (white lines) helping illustrate the relationship between x and y-axis values.

Extended Data Fig. 6 | Neglecting relationships between posterior parameter estimates increases probabilistic temperature projection uncertainty. a-c, Modeled annual average global surface temperature anomalies relative to the 1861-1880 mean using the S-FAIR (purple), S-FUND (teal), and S-Hector (red) climate models. Yellow circles represent temperature observations and solid black center line depicts the mean baseline response across 100,000 model runs. Colored regions outlined by dashed lines span the 95% predictive credible interval. The outer gray colored regions bound the 95% predictive credible intervals for model projections that remove parameter relationships by sampling each marginal posterior distribution independently. The inset figures depict estimated temperature distributions for 2050 and 2100 using the full set of model runs from the baseline (colored) and no parameter relationship (gray) scenarios.

Extended Data Fig. 7 | Strong positive relationship between the SC-CH4 and ECS under the U.S. SC-CH4 estimation framework. **a**, Solid colored lines depict posterior ECS distributions for the S-FAIR (purple), S-FUND (teal), S-Hector (red), and S-MAGICC (orange) climate models. The dark gray dashed line shows the ECS distribution used for official U.S. SC-CH4 estimates. Colored star shapes along the x-axis identify the estimated mean for the different distributions. **b-e**, SC-CH4 vales estimated for a constant 3% consumption discount rate under RCP8.5 following the U.S. SC-CH4 estimation framework's treatment of parametric climate uncertainty. ECS values are sampled from the same distribution used to estimate the U.S. SC-CH4 values. Other uncertain climate model and statistical process parameters remain fixed at their posterior mean values. Each panel depicts 2,000 randomly selected SC-CH4 estimates for DICE (circles) and FUND (diamonds), with loess-smoothed curves (white lines) helping illustrate the relationship between the ECS and SC-CH4.

Extended Data Table Titles and Footnotes

Extended Data Table 1 | Past SC-CH4 estimates and their treatment of parametric climate uncertainty

This table has been adapted from Table 1 in ref. [10] to highlight SC-CH4 estimates from previous studies[6–10] that also account for parametric climate uncertainties. All SC-CH4 values have been converted to 2007 U.S. dollars. The values in the second column show a study's central SC-CH4 estimate, with lower values in parenthesis corresponding to the 95th percentile estimate when reported.

Extended Data Table 2 | Uncertain climate model and statistical process parameters with their prior distributions

* We follow ref. [17] and scale CO_2 radiative forcing in all time periods to be consistent with the sampled forcing increase from CO_2 doubling.
† Uncertain methane cycle parameter in all climate models except S-FUND.
‡ Uncertain methane cycle parameter in S-Hector and S-MAGICC only.
§ Uncertain methane cycle parameter in S-FAIR and S-FUND only.

Descriptions of the uncertain climate model and statistical process parameters. The third column ("Prior Distributions") lists the prior parameter distributions used for the baseline model calibrations. The fourth column ("Wider Prior Distributions") corresponds to an analysis exploring the SC-CH4's sensitivity to model calibrations based on wider and more diffuse prior parameter distributions. Initial conditions refer to the year 1765.

Extended Data Table 3 | Model and scenario specific SC-CH4 estimates

Reported values show the average SC-CH4 estimate for a specific scenario-model combination, with lower values in parenthesis showing the corresponding 5-95% predictive credible interval . The five columns under the RCP8.5 heading depict estimates under constant consumption discounting (2.5%, 3%, and 5%) and Ramsey discounting (pure rate of time preference = 1.5%, elasticity of marginal utility of consumption = 1.0 and 1.5). The remaining columns show alternative SC-CH4 estimates using a constant 3% consumption discount rate for the RCP2.6 scenario ("RCP2.6"), neglecting posterior relationships and sampling each parameter independently ("Neglect Parameter Relationships"), outdated radiative forcing equations that disregard methane's shortwave absorption ("Outdated Methane Forcing"), and sampling the ECS distribution used for U.S. SC-CH4 estimates while fixing other uncertain parameters at their mean posterior values ("U.S. Climate Sensitivity"). The bottom row shows each column's average SC-CH4 estimate.