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Negative emissions to mitigate Earth system risks

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Abstract

Most climate policies are designed under a deterministic Earth system and their climate implications evaluated ex-post. Approaches that incorporate uncertainty ex-ante to anticipate Earth system risks remain underexplored. Here, we derive global climate strategies with an ex-ante approach, employing an integrated assessment framework that embeds estimates of physical uncertainty obtained through Bayesian fusion of Earth system models' and observations' data. These ex-ante strategies mitigate risks in the Earth system through precautionary measures unseen with the ex-post approach, in cost-benefit analysis and cost-effective implementations of various Earth system targets. Net-zero CO2 emissions must typically be reached a decade earlier, which can require up to a doubling of the near-term carbon price. Importantly, sustained and possibly century-long net-negative emissions must be planned for, albeit not to overshoot targets as in traditional scenarios but to mitigate long-term Earth system risks. This heightens the challenge faced by humanity to build a safe future within Earth system boundaries.

Introduction

The exact interference of anthropogenic emissions of greenhouse gases with major Earth system processes remains uncertain. Despite significant progress in understanding climate change over the past decades, precise estimates of key parameters prove elusive: the assessed range of the equilibrium climate sensitivity has seen little reduction throughout six reports by the Intergovernmental Panel on Climate Change[1-6] (IPCC), and the current and future response of the carbon cycle is even more uncertain[7-9]. Given enough time and resources, scientists might reduce these uncertainties to a second-order issue, but urgency dictates that climate policies be designed and implemented now. Physical uncertainty (that is, the uncertainty in the Earth system's response to anthropogenic perturbations) is therefore a first-order consideration[10], especially in light of potentially cascading tipping elements in the Earth system[11]. Policy formulations under the United Nations' Framework Convention on Climate Change do not explicitly address Earth system uncertainties.

Decision theory applied to climate science offers a multitude of approaches to deriving climate mitigation strategies using integrated assessment models (IAMs). Compact IAMs such as the Dynamic Integrated Climate-Economy[12] (DICE) or others[13,14] use a cost-benefit framing that weighs the cost of mitigation against the benefits of avoided economic damages. Technologically detailed IAMs, which informed the sixth assessment report (AR6) of the IPCC[15], follow a cost minimisation philosophy under the constraint of achieving a prescribed climate target. Integrated assessment models can also be differentiated by how they deal with uncertainty in general, and physical uncertainty in particular. The overwhelmingly dominant ex-post approach consists in designing mitigation strategies first and dealing with uncertainty afterwards. In contrast, the ex-ante approach embeds physical uncertainty into the design by building strategies that anticipate their own probabilistic outcomes. The latter mitigates Earth system risks by construction, and ensures the desired targets are strictly met. See Supplementary Note for an intuitive interpretation of the two approaches.

Examples of the ex-post approach are ubiquitous throughout the scientific literature, ranging from simplistic analyses of an optimal strategy's sensitivity to one or a few key parameters[12,14,16], to systematic estimates of ensembles of strategies using Monte Carlo methods[13,17-19]. Conversely, the literature on the ex-ante approach has focused on theoretical aspects and simple illustrative setups[20-23], which has prevented it from being quantitatively relevant and reaching science-policy platforms such as the IPCC. In fact, the current IPCC process is an inconsistent attempt at an ex-ante approach. First, climate scenarios are created using IAMs most often under a single-value constraint (a remaining carbon budget[8]) to meet a global temperature target with a given probability level. This follows the ex-ante philosophy of anticipating uncertainty. Then, these scenarios are projected using reduced-complexity models and Monte Carlo methods[15,24] This provides a probabilistic climate outcome following an ex-post approach. However, the initial constraint and the projections are not linked, which prevents physical information from endogenously feeding back into decision-making and ultimately does not ensure meeting the target. This limitation is solved by construction under our fully fledged ex-ante approach (Methods).

Here, we follow calls for better integration of uncertainty into climate policies and improved economic assessment[10,25,26] by combining a standard IAM and a specifically designed reduced-form model of the carbon-climate system whose calibration embeds the latest knowledge from state-of-the-art Earth system models and observations. We use this model as a unified framework to consistently study risk-mitigating strategies under the ex-ante approach, under different epistemological formulations: cost-benefit and cost-effective analyses, the latter for different Earth system targets including global warming of 2°C and 1.5°C. We quantify the precautionary measures required to address known Earth system uncertainties through more ambitious decarbonisation efforts.

Results

Integrated assessment under uncertainty

Our integrated assessment model combines the DICE model[12], updated following recent recommendations[27] for emissions generation and impact quantification, and the Pathfinder model[28] (Methods) to represent Earth system dynamics and their uncertainty. Pathfinder is a state-of-the-art non-linear carbon-climate model of reduced complexity, carefully designed to avoid excessive computational demand while adequately emulating physical processes. Its parameters are derived using Bayesian inference to merge several data sources: simulations from the Coupled Model Intercomparison Project phase 6 (CMIP6) underlying the AR6, observational data, and complementary assessments such as the Global Carbon Budget[29] and the AR6[6,8,30,31]. This calibration method provides a consistent and unique probability density of maximum likelihood, from which we draw 600 realisations that form our equally probable states of the world (SOWs). This posterior joint distribution of parameters and Pathfinder's ability to produce plausible historical states have been thoroughly validated (ref[28] and Supplementary Table 1).

We simulate optimal mitigation strategies in the DICE-Pathfinder model following the ex-post and ex-ante paradigms (Figure 1). In the ex-post approach, decision variables are specific to each SOW, which provides a probabilistic ensemble of individually optimal strategies. In the ex-ante approach, decision variables are shared across SOWs, which leads to a unique optimal strategy whose outcomes in terms of costs and impacts are anticipated in all SOWs simultaneously. Importantly, our implementation of the ex-ante approach does not consider endogenous scientific learning, which means the uncertainty itself remains unchanged within the simulation's horizon. This assumption is discussed hereafter, but we note here that it is firstly motivated by the impossibility to know the future learning rate or the outcome of this learning.

Cost-benefit analysis

Cost-benefit analysis (CBA) weighs the costs of mitigating emissions against avoided economic damages caused by climate change, through maximisation of a discounted utilitarian welfare function. CBA is one of the main ways to estimate the social cost of carbon[12], defined as the cost to society of emitting one extra tonne of carbon along a given pathway[32]. In the ex-post approach, the welfare in each SOW is maximised independently. In the ex-ante approach, the expected welfare is maximised via shared decision variables (which is known as the expected utility criterion[33,34]) so that risks are mitigated by optimally transferring costs and damages across SOWs.

Figure 2 (panels a, d, g) compares the optimal pathways resulting from ex-post and ex-ante CBA, and Table 1 compiles key related values. Under the ex-post approach, warming peaks at 1.6 (1.4, 1.8) °C (median and 90% confidence interval; mean of 1.6 °C), while under the ex-ante approach, it peaks sooner and lower at 1.5 (1.3, 1.7) °C (mean of 1.5 °C). While seemingly small, this 0.1 °C difference is a significant additional effort achieved by reaching net-zero CO2 emissions in 2041, which is about two decades earlier than the median (or the mean) of the ex-post ensemble. Consequently, the carbon price in 2030 is 425 USD per tCO2 (United States Dollars per tonne of CO2) in the ex-ante approach, which is above the 99th percentile of the distribution of carbon prices in the ex-post approach. (Note that the absence of a carbon price distribution in the ex-ante approach is a direct consequence of the unicity of the shared decision variables). The corresponding short-term emission budget (defined as cumulative CO2 emissions before reaching net zero) is ~50% smaller in the ex-ante approach, and in the long term, preindustrial temperature is restored within ~200 years following the peak, sooner than in almost all individual SOWs in the ex-post approach. This climate restoration requires maintaining a steady and substantial amount of net-negative emissions for two centuries.

The ex-ante approach generates strategies that exhibit significantly more risk aversion than in the ex-post ensemble. In our model, there are two sources of risk aversion: convex climate damage and concave utility functions entail disproportionally higher welfare loss in high-warming SOWs, even if all outcomes are equally likely. This in turn leads to earlier and stronger mitigation to avoid these particularly unfavourable SOWs, as well as an increase of the carbon price (akin to an insurance premium) until near climate restoration. CBA trades off the costs of damage in unfavourable high-damage SOWs against the costs of higher mitigation in favourable low-damage SOWs. Therefore, favourable SOWs have carbon prices above their own optimal value to spread the burden of unfavourable climate outcomes across the probability space, which is not allowed in the ex-post approach. This is in qualitative agreement with earlier studies[21,33,34], but here quantitative implications are based on state-of-the-art physical science.

Cost-effective climate targets

CBA has been criticised, notably for its reliance on poorly known estimates of economic damages and its neglect of unpriceable impacts[35]. An alternative epistemological formulation, which is in line with the Paris climate agreement and IPCC scenarios, minimises the cost of not crossing the threshold of an agreed climate target. In the ex-post approach, the absence of uncertainty implies that the target is met in each individual SOW if at all feasible. In the ex-ante approach, the target is defined probabilistically so that a chosen fraction of SOWs is to remain within the boundary, and this fraction is therefore the confidence level of meeting the target. Importantly, SOWs in which it is impossible to meet the target do not bring any information under the ex-post approach, since the optimisation simply fails, whereas they still do under the ex-ante approach.

Figure 2 (panels b, e, h and c, f, i, respectively) and Table 1 show cost-effective mitigation strategies for the 2 °C and 1.5 °C global warming targets. In the short term, efforts required to stay below 2 °C appear similar in both approaches. Comparing the 50% confidence level of the ex-ante approach with the median of the ex-post approach, net zero emission is advanced by only three years, which reduces the short-term emission budget by 200 GtCO2 and requires a modest carbon price increase of +8% in 2030. Differences are of the same order of magnitude between the 95% confidence level (ex-ante) and the 95th percentile (ex-post). For the 1.5 °C target, however, the two approaches differ drastically. At the 50% confidence level, the year of net zero is brought forward by 35 years, which effectively halves the short-term emission budget, and the 2030 carbon price increases by +64%. Staying below 1.5 °C with 95% confidence is found unfeasible under our updated technological assumptions[27].

Long-term mitigation strategies differ between approaches. The ex-post approach maintains temperature at the targeted level in the absence of further incentive, while the ex-ante one makes it depart from this level after reaching it (Figure 2 and Supplementary Figure 1). This risk-averse behaviour is motivated solely by physical considerations (contrarily to CBA), as it is a precaution against slow-warming SOWs whose peak will occur later, enabled by anticipating the distribution of the Earth system's response. This requires planning for substantial net-negative emissions for the foreseeable future, as illustrated by the negative long-term emission budgets (defined as cumulative CO2 emissions from present days to 2500) of Table 1.

Investigating Earth system targets

To further investigate the difference between ex-post and ex-ante approaches, we repeat cost-effective experiments for other Earth system targets that showcase differing physical properties and levels of scientific understanding (Figure 3 and Supplementary Figure 1).

The first such target is permafrost thaw, which is a process further down the climatic cause-effect chain that impacts local infrastructures[36] and communities, and a feedback that amplifies global warming in a non-linear fashion[8,37]. In the absence of internationally recognised targets, we tested arbitrary thawing limits of 30%, 40% or 50% of the global preindustrial frozen carbon pool. As with temperature targets, we find that the additional mitigation effort required by risk-mitigating (that is, ex-ante) strategies increases for more stringent permafrost targets. This additional effort, however, appears greater for a given permafrost target than for a comparable temperature target. For instance, as a proxy for short-term mitigation effort, the 2030 carbon price increase to keep permafrost carbon thaw below 30% with 66% confidence is +138% (+188 USD per tCO2). This requires a median temperature peak of 1.5 °C (Supplementary Table 2) and can therefore be compared to the 2030 carbon price increase of +64% (+154 USD per tCO2) to keep temperature below 1.5 °C with 50% confidence. The larger price increase is explained by the much larger physical uncertainty in the future response of the permafrost system that requires greater precautionary measures (in other words, a higher insurance premium) to mitigate potential risks.

We also test two global ocean-related targets: surface acidification and speed of sea level rise (SLR). The former is further up the cause-effect chain (that is, it happens before warming because it is driven by increased atmospheric

CO_2 concentration) and therefore exhibits lower overall uncertainty; its target is set to −0.2 pH unit, which is a coarse proxy threshold assumed to prevent a breakdown of marine ecosystems[16,38,39]. Speed of SLR is a climate impact that exhibits high uncertainty; its target is set to 5 cm per decade, which has been suggested as a threshold to allow time for implementation of adaptation measures[16,38]. As expected, the carbon price increase to mitigate risks is fairly small for the acidification target, reaching only +4% for a 95% confidence level. The carbon price increase for the SLR speed target, however, is also small despite a significantly higher physical uncertainty, which is explained by the impact's reversibility (because it is the speed and not the absolute sea level) that leaves open more possible pathways for mitigation and therefore reduces the need for precautionary measures.

From these tests, summarised in terms of carbon price in 2030 in Figure 4, we conclude that the additional mitigation efforts required on the short-term to meet a given probabilistic Earth system target are commensurate to the target's stringency, to its degree of irreversibility, and to our lack of scientific understanding of the physical processes involved.

Discussion

We developed a unifying framework that transcends the various system boundaries and objective functions used by stylised IAMs, to systematically assess the impact of ex-ante inclusion of physical uncertainty into climate mitigation strategies. We found that risk-mitigating strategies need to systematically ramp up and sustain mitigation efforts, regardless of whether we use CBA or a cost-effectiveness framing. Ramping up means near-immediate peak of emission, very rapid decarbonisation, and early and sustained deployment of negative emission technologies to avoid deleterious Earth system outcomes.

We have deliberately limited this study to physical uncertainty and the expected utility criterion to fully leverage the Bayesian-inferred Pathfinder model. It is nonetheless possible to extend our work to socio-economic uncertainty, provided probability distributions of parameters are available, which may be controversial for those pertaining to ethical judgement such as the social discount rate[40,41]. Alternative ex-ante decision-making algorithms[10,20,22,42-44] could partially solve this, help account for structural modelling uncertainty, or even endogenise scientific learning, albeit at the cost of having to set arbitrary parameters such as ambiguity aversion[45] or penalties in the objective function[46]. All these would increase the premium required to mitigate risks[22,42], as would integration of other tipping elements into our work[18], which renders our estimates conservative.

Specifically, the lack of scientific learning does not prevent drawing policy-relevant insights from our experiments[10]. First, international climate agreements require a cessation of emissions within decades, while past scientific progress in resolving parameter uncertainty over a similar time span has been limited, as illustrated with the equilibrium climate sensitivity. Moreover, a low-warming world compatible with the Paris agreement may well keep the signal-to-noise ratio of anthropogenic climate change below what could provide additional constraints, as is the case nowadays for certain physical variables and regions of the world[47]. It is therefore distinctly possible that we will never be able to determine the true value of key Earth system parameters. Second, without knowledge of the true Earth system, the implementation of learning requires arbitrary decisions as to what will be learnt and when[43,44], turning a quantitative modelling exercise into non-actionable what-if scenarios. Since climate policies must be designed now with today's best available knowledge, assuming no significant scientific learning follows the precautionary principle. Third, even if it could be implemented in a reasonable way, learning would have to be very fast to significantly influence key short-term variables such as the year of net zero emission or the 2030 carbon price. We do acknowledge that learning would affect long-term variables, however. Given that ex-post and ex-ante correspond to the two extreme assumptions of instantaneous learning and lack thereof, respectively, an implementation of learning would result between both cases, progressively moving from the ex-ante to the ex-post pathways as learning happens (without prior knowledge of what will be learnt). This implies that our results are estimates of what should be planned for, which could be revised as new information becomes available.

Our pathways are broadly in line with the IAM scenarios assessed in the AR6[15] (Supplementary Figure 2). The ones we obtain with the ex-ante approach notably exhibit a peak-and-decline behaviour found in many low-warming IAM scenarios. However, the fundamental cause for this behaviour differs. In traditional IAMs, peak-and-decline is caused by setting end-of-century targets that allow a temporary overshoot, whereas in our risk-mitigating pathways, the targets are never overshot and the peak-and-decline is needed to reduce the risk of crossing the threshold. In other words, traditional pathways use net-negative emissions to postpone costly short-term mitigation (following discounting principles[48,49]), while ours use them as a risk mitigation measure[50]. This provides a formal justification to what others have concluded empirically: preventive carbon dioxide removal capacity are required to hedge against high-risk climate outcomes[51].

Besides, our assessment of the feasibility of very stringent targets (1.5 °C or 30% of permafrost carbon thawed) is strongly dependent on the simplistic techno-economic assumptions of DICE regarding hard limits on abatement level, decarbonisation rate, and negative emissions availability. It is therefore a logical next step to apply the ex-ante approach using technologically detailed IAMs that typically contribute to IPCC reports. To this end, efforts to integrate knowledge and modelling across IPCC working groups must be strengthened, so that emulators of complex Earth system models and their uncertainties are coupled to IAMs during scenario design.

Beyond methodological improvement, our results demonstrate the necessity to recognise our imperfect scientific knowledge about the Earth system in the formulation of strategies to fight climate change or stay within planetary boundaries[52]. Risk-mitigating strategies entail significant carbon price increases in the short term, commensurate to our current inability to accurately predict Earth system dynamics. These precautionary premiums are equivalent to a measure of the economic value of knowledge and are indicative of the potential benefits from improved understanding through increased scientific efforts and research investments. These strategies also demand planning for sustained net-negative emissions to bring the Earth system away from dangerous thresholds. In other words, negative emissions should be seen as a safety net against unfavourable outcomes of the Earth system, and not as an excuse to delay mitigation efforts and overshoot climate targets. Under conventional carbon pricing instruments, these net-negative emissions translate into unrealistic levels of public subsidies[53]. New financial mechanisms are therefore needed to ensure operationalisation of a net-negative carbon economy[54], notably global institutions and equity arrangements that remain to be built and should last centuries.

Methods

The Pathfinder model

We use v1.0 of the Pathfinder model, whose comprehensive description is provided in ref[28] and briefly summarized here. The model is a compilation of existing formulations describing the climate and carbon cycle systems, chosen for their balance between mathematical simplicity and physical accuracy. The climate subcomponent that links global surface air temperature (GSAT) to effective radiative forcing (ERF) follows a widely used 2-box model with deep ocean heat uptake efficacy[55]. We note this is a structure similar to that of the original DICE, albeit with time-dependent climate feedback factor[56] and drastically revised parameters' values. The total ERF is caused by atmospheric CO_2 (following the IPCC AR5 logarithmic formula[57]) and an aggregate of non-CO_2 species (provided as exogenous time series). Atmospheric CO_2 is calculated as the balance between industrial CO_2 emissions (determined by the economic module), land use CO_2 emissions (provided as exogenous time series), ocean and land carbon sinks, and permafrost carbon emissions. The ocean carbon cycle follows the structure of the Bern Simple Climate Model[58]. The land carbon cycle follows the formulation of the compact Earth system model OSCAR[59], although it is aggregated into one global biome, land use change is ignored, and a fraction of soil carbon pool is assumed passive[60]. Emissions from permafrost thaw are calculated with the emulator from ref[37], but aggregated into one unique region. Sea level rise (SLR) is split into a thermosteric contribution and three ice-related ones: glaciers, Greenland ice sheets, and Antarctica ice sheets. The thermosteric effect is a linear function of the oceanic heat content[30,61], and each ice-related effect follows a first-order differential equation[62] driven by a non-linear function of GSAT change. Additionally, ocean surface acidification follows a polynomial fit on atmospheric CO_2 concentration[63].

Bayesian calibration

Bayesian inference allows assimilating observational data into reduced-complexity models such as Pathfinder[64]. Conceptually, posterior probability distributions of parameters are deduced by merging a priori knowledge on the distributions of these parameters and on distributions of observations of some of the model's simulated variables, using Bayes' law[65]. Mathematically, the posterior probability $\mathcal{P}_{\text{post}}$ of a given sample k from the parameters' joint distribution $\boldsymbol{\theta}$, conditional on a set of constraints $\boldsymbol{x}$, is proportional to the prior probability $\mathcal{P}_{\text{pre}}$ of drawing k, to the likelihood $\mathcal{L}$ of the model simulating $\boldsymbol{x}$ given k, and to a normalization factor $\mathcal{N}$, following equation (1).

$$\mathcal{P}_{\text{post}}(\boldsymbol{\theta_k}|\boldsymbol{x}) = \mathcal{L}(\boldsymbol{x}|\boldsymbol{\theta_k})\,\mathcal{P}_{\text{pre}}(\boldsymbol{\theta_k})\,\mathcal{N} \quad (1)$$

Complete details of the calibration setup are provided in ref[28], and key aspects follow. The overarching calibration philosophy is to use state-of-the-art complex models' outputs as prior information and only real-world observations or assessments combining many lines of evidence as constraints. The calibration procedure was numerically implemented using the PyMC3 Python package[66], and a full-rank Automatic Differentiation

Variational Inference algorithm[67] that provides correlated (i.e. joint) posterior distributions even if the prior ones are uncorrelated.

In Pathfinder v1.0, the $\boldsymbol{\theta}$ vector is made of 44 physical parameters and 6 parameters used to generate random historical time series of GSAT and atmospheric CO2 (while an additional 33 parameters are fixed). Prior distributions of the physical parameters are deduced from multi-model ensembles for 35 of them, taken from the literature for another eight parameters, and arbitrarily assumed for only one. Specifically, outputs from the Coupled Model Intercomparison Project phase 6 (CMIP6) were used for parameters of the climate response (from 35 models[68]), as well as for parameters of the ocean and land carbon cycles (12 models[7]), while TRENDYv7 data[69] was used for parameters of the preindustrial land carbon cycle (11 models[70]), and the permafrost parameters were based on ref[37] (5 models).

The $\boldsymbol{x}$ vector is made of 19 constraints, many of which are observations, but some are ranges assessed by expert panels such as the Global Carbon Project or the IPCC. The climate response was constrained using observed GSAT (present-day value and derivative across five datasets[71-75]), assessed ocean heat uptake[31], non-CO2 effective radiative forcing[6], and equilibrium climate sensitivity[6,76]. The global CO2 budget was constrained using observed atmospheric concentration[77], and the Global Carbon Budget[29] assessment (for anthropogenic emissions, land and ocean sinks, and atmospheric growth). The land carbon cycle was further constrained using estimates of net primary productivity[78,79], and preindustrial vegetation and soil carbon pools[8,79] (the latter was corrected for carbon in peatland[80]). The SLR module was constrained using historical sea level inferred from tide gauges[30] (corrected for the missed impact of uncharted glaciers[81]), modelled estimates of SLR speed for all four contributions[30], and an estimate of the SLR caused by the little ice age relaxation[82].

Coupling with DICE

Our version of DICE is the published DICE-2016R2 version[12] with the following additional updates[27]: economic damage function[83], pure rate of time preference and intertemporal elasticity of substitution[84], and constraints on technical feasibility (emissions reduction of no more than 10 GtCO2 per 5-year period, abatement rate increase of at most 10% per 5-year period, and availability of net-negative emissions technology as of 2045).

The updated DICE is coupled with Pathfinder, whose differential system is discretised using a backward Eulerian scheme (with the 5-year time step of the original DICE). DICE feeds emissions to Pathfinder which hands GSAT change back to DICE. To initialise the model in 2015 (the base year), we use the state and forcing variables from the historical run of the calibration, averaged over 2013-2017.

For any given set of parameters and corresponding initial states, also called a “configuration” or “state of the world” (SOW, subscript s) in main text, the final discretized coupled dynamic system is shown in equation (2).

$$\begin{cases} K_{s,t+\delta t} = (1-\nu_K)^{\delta t} K_{s,t} + \left(1 - D\left[T_{s,t}\right] - M\left[\mu_{s,t}, t\right]\right) Y\left[K_{s,t}, t\right] - C_{s,t} \\ E_{s,t} = \left(1-\mu_{s,t}\right) e_t Y\left[K_{s,t}, t\right] + L_{s,t} \\ T_{s,t} = f_s \left[\left\{E_{s,\tau}\right\}_{\tau=1751}^{t}, \left\{F_{s,\tau}\right\}_{\tau=1751}^{t}\right] \end{cases} \tag{2}$$

K is the economic capital, T the GSAT change, μ the abatement rate (with respect to the baseline industrial emissions), C the consumption of economic capital, E the annual anthropogenic CO_2 emissions, e the economy's carbon intensity, L the land use change CO_2 emissions, and F the non-CO_2 ERF. The function D represents the economic damage caused by climate change, M the mitigation cost fraction, Y the economic production (that follows a Cobb-Douglas function[85] with constant elasticity of substitution), and f the physical Earth system (i.e. the Pathfinder model). The subscript t is time, δt is the time step (5 years), and ν_K is the depreciation rate of capital. Note that μ and C are the two control variables that are chosen during optimisation of the system.

Exogenous time series

DICE-Pathfinder is forced by a number of exogenous variables prescribed as time series. Total factor productivity and world population (both used in Y), carbon intensity of the economy, and price of the backstop technology (used in M), all follow ref[12]. The remaining two forcings, however, are reformulated and recalibrated to match the physical module and its probabilistic formulation, notably so that initial values are consistent with parameters values (e.g. high equilibrium climate sensitivity and strong aerosol cooling are more likely to occur together across SOWs).

Land use change emissions are assumed to follow an exponential decrease (with rate κ_L) starting from an initial value in year 2015. We calculate this initial value by taking the total anthropogenic CO_2 emissions coming out of our calibration and subtracting the central estimate for fossil fuel emissions over 2010-2019 of the Global Carbon Budget[86] (noted E^*), which leads to equation (3).

$$L_{s,t} = \left(E_{s,2015} - E^*\right) \exp\left(-\kappa_L (t - 2015)\right) \tag{3}$$

Non-CO_2 ERF is split in two additive terms: one for greenhouse gases including ozone (noted G) and one for the rest, mostly aerosols (noted A). We then introduce a reference value for the ERF of greenhouse gases (F^*) that depends on the SOW, taken as a normal distribution with mean value of 1.60 W m^{-2} and standard deviation of 0.26 W m^{-2} (ref[68]). The aerosols term is then assumed to converge exponentially (with rate κ_A) to a non-zero fraction of its initial value (π_A), as in equation (4).

$$A_{s,t} = \left(F_{s,2015} - F_s^*\right)\left((1-\pi_A) \exp\left(-\kappa_A (t-2015)\right) + \pi_A\right) \tag{4}$$

The greenhouse gases term is also assumed to converge exponentially (with rate κ_G) to a fraction of its initial value (π_G), although it is also assumed to have an initial linear trend (ν_G), as in equation (5).

$$G_{s,t} = F_s^* \left(\left(1 - \pi_G + \nu_G(t - 2015)\right) \exp\left(-\kappa_G(t - 2015)\right) + \pi_G \right) \tag{5}$$

The six parameters needed to generate these time series are calibrated on the SSP scenarios[87] database. We take all available scenarios that lead to a relatively low warming, corresponding to radiative forcing targets of 1.9, 2.6, 3.4 and 4.5 W m^{-2}. Using the relative values extracted from the database of L, G, and A with respect to 2015, we fit the parameters' values to minimize the distance between the fitted function and all the scenarios, with an ordinary least-square method, as shown in Supplementary Figure 3. This led to κ_L = 0.077 yr^{-1}, κ_A = 0.025 yr^{-1}, π_A = 0.32, κ_G = 0.047 yr^{-1}, ν_G = 0.031 yr^{-1} and π_G = 0.54. The resulting L and F trajectories across SOWs are also shown in Supplementary Figure 3. We note that L is consistent with a mid-range interpretation of the Glasgow commitment on deforestation[88].

Ex-post approach

As with the original DICE, control variables are chosen to maximise utilitarian welfare in every SOW separately; that is, the social planner looks for all $C_{s,t}$ and $\mu_{s,t}$ that meet equation (6).

$$\max_{\{\mu_{s,t}\}_t, \{C_{s,t}\}_t} \sum_{t=2015}^{\tau_H} \beta^{\Delta t} U\left[C_{s,t}, t\right] \tag{6}$$

Total welfare is the sum up to a time horizon (τ_H = 2510) of the product of a discounting function ($\beta^{\Delta t}$) and a utility function (U) that is monotonically increasing with C. In the cost-benefit experiments, a non-trivial optimum is reached because increased consumption (desirable to maximize welfare at time t) is counter-balanced by increased economic damage (that reduces potential consumption later on), and it is therefore necessary to invest in mitigation to prevent the damage. In the cost-effective experiments, damages are set to zero ($D \equiv 0$) but targeted physical variables are capped at the target level. Because the solver used for optimisation performs significantly worse for abrupt (i.e. non-differentiable) functions, this capping mechanism is added to the system's utility as a penalty term. For instance, for a temperature target of T^*, the objective function becomes equation (7).

$$\max_{\{\mu_{s,t}\}_t, \{C_{s,t}\}_t} \sum_{t=2015}^{\tau_H} \beta^{\Delta t} U\left[C_{s,t}, t\right] - \alpha_{pen} \left(\max_t T_{s,t} - T^* \right)^2 \tag{7}$$

α_{pen} is the penalty parameter (taken as 10^6 for temperature targets, and 10^9 otherwise), and the maximum is determined during optimisation as the upper bound of $T_{s,t}$ for all t and any given s. This approximation leads to very minor numerical inaccuracy, as illustrated in the resulting constrained pathways displayed in Supplementary Figure 4.

Ex-ante approach

The risk-mitigating social optimum maximizes the expected utilitarian welfare across SOWs; that is, the social planner looks for a unique pair of $\tilde{C}_t$ and $\tilde{\mu}_t$, at every time *t*, that meet equation (8), with the additional constraints for all *t* and *s* of equation (9).

$$\max_{\{\mu_{s,t}\}_t,\{C_{s,t}\}_t} \frac{1}{n_s}\sum_{s=1}^{n_s}\sum_{t=2015}^{\tau_H} \beta^{\Delta t} U\left[C_{s,t}, t\right] \tag{8}$$

$$\begin{cases} C_{s,t} = \tilde{C}_t \\ \mu_{s,t} = \tilde{\mu}_t \end{cases} \tag{9}$$

n_s is the number of SOWs in our experiments.

In the cost-benefit experiments, the overall dynamic follows that of the ex-post approach, with the added constraint that all SOWs share the same control variables, implying that all their future responses are simultaneously anticipated by the social planner. We note that the welfare criterion of equation (8) could be expanded to account for ambiguity aversion[45], which would give more importance to the least desired SOWs and, therefore, further increase insurance premiums to favour a precautionary optimum.

In the cost-effective experiments, the ex-ante and ex-post approaches are more dissimilar, as we do not force all SOWs to stay below the chosen targets. (This would essentially reduce the ex-ante approach to taking the worst possible SOW of the ex-post approach.) Instead, we express the target in a probabilistic fashion, so that a fraction (p^*) of SOWs should meet the target; leading to the additional inequation (10).

$$\frac{1}{n_s}\sum_{s=1}^{n_s}\left[\!\left[\max_t T_{\mathrm{s,t}} > T^*\right]\!\right] \leq p^* \tag{10}$$

where double brackets are used as Iverson brackets that take a value of 1 if the bracketed statement is true and 0 otherwise. To avoid non-differentiable function, we implement the logical test in Iverson brackets using a sigmoid approximation, shown in equation (11).

$$\left[\!\left[\max_t T_{\mathrm{s,t}} > T^*\right]\!\right] \simeq \frac{1}{1+\exp\left(-\alpha_{\mathrm{sig}}\left(\max_t T_{\mathrm{s,t}} - T^*\right)\right)} \tag{11}$$

$\alpha_{\mathrm{sig}} = 100$ (or 500 for the pH constraint). Both approximations lead to very minor numerical deviations, as illustrated in Supplementary Figure 5.

Carbon pricing

The maximisation problem described hereinabove is solved using the GAMS programming language, and the CONOPT4 NLP solver. Ignoring inequality constraints for ease of exposition, the Lagrangian of the optimisation problem in the ex-ante approach yields the following first-order conditions summarized in equations (12) to (15):

$$U'\left[\tilde{C}_t, t\right] = \frac{1}{n_s}\sum_{s=1}^{n_s} \lambda_{s,t} \tag{12}$$

$$\lambda_{s,t-\delta t} = \beta\lambda_{s,t}\left((1-\nu_K)^{\delta t} + \left(1 - D\left[T_{s,t}\right] - M\left[\mu_{s,t}, t\right] - \frac{\eta_{s,t}}{\lambda_{s,t}}(1-\tilde{\mu}_t)e_t\right)Y'\left[K_{s,t}, t\right]\right) \tag{13}$$

$$\eta_{s,t} = \sum_{\tau=t}^{\tau_H} \beta^{\tau-t}\lambda_{s,\tau}D'\left[T_{s,\tau}\right]Y\left[K_{s,\tau}, \tau\right]\frac{\partial T_{s,\tau}}{\partial E_{s,t}} \tag{14}$$

$$M'[\tilde{\mu}_t, t]\sum_{s=1}^{n_s} \lambda_{s,t}Y\left[K_{s,t}, t\right] = e_t\sum_{s=1}^{n_s} \eta_{s,t}Y\left[K_{s,t}, t\right] \tag{15}$$

The prime symbol (′) designates the first derivative of a function with respect to its non-time variable, and $\lambda_{s,t}$ and $\eta_{s,t}$ are the Lagrange multipliers (also called shadow values) for $K_{s,t}$ and $E_{s,t}$, respectively.

These equations are interpreted as follows. In choosing optimal consumption, the marginal benefit of using output for consumption at time t has to equal the benefit of transferring this output into the future, which equation (12) shows is equal to the expected shadow value of capital across SOWs. Equation (13) defines the shadow value of capital as the present-discounted future marginal output of an extra unit of capital minus the cost of the marginal emission caused by this unit of capital. Equation (14) defines the shadow value of emissions as the present-discounted sum of all future marginal production damages caused by emitting an extra ton of CO2 at time t. Finally, equation (15) represents the optimal carbon price being set such that the expected cost of abatement equals the expected benefit.

Using the first-order condition for abatement formulated in equation (15), we recover the risk-mitigating carbon price (noted χ), which itself is uniform across SOWs and equals the marginal cost of abatement, following equation (16).

$$\chi_t = \frac{M'[\tilde{\mu}_t, t]}{e_t} = \frac{\sum_{s=1}^{n_s} \eta_{s,t}Y\left[K_{s,t}, t\right]}{\sum_{s=1}^{n_s} \lambda_{s,t}Y\left[K_{s,t}, t\right]} \tag{16}$$

This carbon price is therefore calculated as the ratio of the weighted average across SOWs of two Lagrange multipliers. Setting $n_s = 1$ immediately gives the usual definition of the social cost of carbon in the DICE model as the ratio of two (simple) Lagrange multipliers[12]. We further note that when inequality constraints (such as boundaries to μ) are binding, equation (16) does not hold, and the social cost of carbon defined as the weighted ratio of the Lagrange multipliers is not equal to the marginal cost of mitigation.

All prices are reported in constant 2015 US$ per tonne of CO2 (USD $tCO2^{-1}$).

Number of SOWs

To retain numerical solvability of the large mathematical system optimized in this work, we limited the number of SOWs to n = 600. We note that this amount of ensemble members is being used with other simple climate models[24,89] and is expected to provide a reasonable approximation of the actual probability distribution of the results according to the theory[90]. Nevertheless, we tested the effect of this choice on our results for the CBA and one cost-effective experiment (2 °C with 66% confidence). We repeated these experiments with m = 50 different draws from the posterior joint distribution of Pathfinder's parameters and initial states, for a progressively increasing value of n. Supplementary Figure 6 shows the convergence above a few hundreds of SOWs. We conclude that our results with the ex-ante approach – including the unique carbon price – exhibit a relative uncertainty of less than 5% (1 standard deviation).

Data availability

The data generated in this study is available for download at https://zenodo.org/records/18461481[91].

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Code availability

Original code of DICE-2016R2 unavailable publicly; code of a subsequent version available at https://www.openicpsr.org/openicpsr/project/114711/version/V1/view. Code of a stand-alone version of Pathfinder (in Python), along with all input data used for calibration, available at https://zenodo.org/records/7194161[92]. GAMS code of our simulations available at https://github.com/ComeCheritel/pathfinder_dice.

References

1 Mitchell, J. F. B., Manabe, S., Meleshko, V. & Tokioka, T. in *Climate Change: The IPCC Scientific Assessment* (eds J.T. Houghton, G.J. Jenkins, & J.J. Ephraums) Ch. 5, 131–172 (Cambridge University Press, 1990).

2 IPCC. in *Climate Change 1995: The Science of Climate Change. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change* (eds J.T. Houghton *et al.*) Ch. TS, 9–50 (Cambridge University Press, 1995).

3 Albritton, D. L. *et al.* in *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (eds J.T. Houghton *et al.*) Ch. TS, 21–84 (Cambridge University Press, 2001).

4 Meehl, G. A. *et al.* in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (eds S. Solomon *et al.*) Ch. 10, 747–845 (Cambridge University Press, 2007).

5 Collins, M. *et al.* in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds T.F. Stocker *et al.*) Ch. 12, 1029–1136 (Cambridge University Press, 2013).

6 Forster, P. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte *et al.*) Ch. 7, 923–1054 (Cambridge University Press, 2021).

7 Arora, V. K. *et al.* Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models. *Biogeosciences* **17**, 4173-4222, doi:10.5194/bg-17-4173-2020 (2020).

8 Canadell, J. G. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte *et al.*) Ch. 5, 673–816 (Cambridge University Press, 2021).

9 Friedlingstein, P. *et al.* Global Carbon Budget 2023. *Earth Syst. Sci. Data* **15**, 5301-5369, doi:10.5194/essd-15-5301-2023 (2023).

10 Barnett, M., Brock, W. & Hansen, L. P. Pricing Uncertainty Induced by Climate Change. *The Review of Financial Studies* **33**, 1024-1066, doi:10.1093/rfs/hhz144 (2020).

11 Lenton, T. M. *et al.* Climate tipping points — too risky to bet against. *Nature* **575**, 592-595, doi:10.1038/d41586-019-03595-0 (2019).

12 Nordhaus, W. D. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences* **114**, 1518-1523, doi:10.1073/pnas.1609244114 (2017).

13 Hope, C. The Marginal Impact of CO2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern. *Integrated Assessment Journal* **6**, 19-56 (2006).

14 Anthoff, D. & Tol, R. S. J. The uncertainty about the social cost of carbon: A decomposition analysis using FUND. *Climatic Change* **117**, 515-530, doi:10.1007/s10584-013-0706-7 (2013).

15 Riahi, K. *et al.* in *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds P.R. Shukla *et al.*) Ch. 3, 295–408 (Cambridge University Press, 2022).

16 Kvale, K. *et al.* Carbon Dioxide Emission Pathways Avoiding Dangerous Ocean Impacts. *Weather, Climate, and Society* **4**, 212-229, doi:10.1175/WCAS-D-11-00030.1 (2012).

17 Gillingham, K. *et al.* Modeling Uncertainty in Integrated Assessment of Climate Change: A Multimodel Comparison. *Journal of the Association of Environmental and Resource Economists* **5**, 791-826, doi:10.1086/698910 (2018).

18 Dietz, S., Rising, J., Stoerk, T. & Wagner, G. Economic impacts of tipping points in the climate system. *Proceedings of the National Academy of Sciences* **118**, e2103081118, doi:10.1073/pnas.2103081118 (2021).

19 Errickson, F. C., Keller, K., Collins, W. D., Srikrishnan, V. & Anthoff, D. Equity is more important for the social cost of methane than climate uncertainty. *Nature* **592**, 564-570, doi:10.1038/s41586-021-03386-6 (2021).

20 Heal, G. & Millner, A. Reflections: Uncertainty and Decision Making in Climate Change Economics. *Review of Environmental Economics and Policy* **8**, 120-137, doi:10.1093/reep/ret023 (2014).

21 Jensen, S. & Traeger, C. P. Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings. *European Economic Review* **69**, 104-125, doi:10.1016/j.euroecorev.2014.01.008 (2014).

22 Berger, L. & Marinacci, M. Model Uncertainty in Climate Change Economics: A Review and Proposed Framework for Future Research. *Environmental and Resource Economics* **77**, 475-501, doi:10.1007/s10640-020-00503-3 (2020).

23 Rudik, I. Optimal Climate Policy When Damages Are Unknown. *American Economic Journal: Economic Policy* **12**, 340-373, doi:10.1257/pol.20160541 (2020).

24 Kikstra, J. S. *et al.* The IPCC Sixth Assessment Report WGIII climate assessment of mitigation pathways: from emissions to global temperatures. *Geosci. Model Dev.* **15**, 9075-9109, doi:10.5194/gmd-15-9075-2022 (2022).

25 Burke, M. *et al.* Opportunities for advances in climate change economics. *Science* **352**, 292-293, doi:10.1126/science.aad9634 (2016).

26 Wagner, G. *et al.* Eight priorities for calculating the social cost of carbon. *Nature* **590**, 548-550, doi:10.1038/d41586-021-00441-0 (2021).

27 Hänsel, M. C. *et al.* Climate economics support for the UN climate targets. *Nature Climate Change* **10**, 781-789, doi:10.1038/s41558-020-0833-x (2020).

28 Bossy, T., Gasser, T. & Ciais, P. Pathfinder v1.0.1: a Bayesian-inferred simple carbon–climate model to explore climate change scenarios. *Geosci. Model Dev.* **15**, 8831-8868, doi:10.5194/gmd-15-8831-2022 (2022).

29 Friedlingstein, P. *et al.* Global Carbon Budget 2021. *Earth Syst. Sci. Data* **14**, 1917-2005, doi:10.5194/essd-14-1917-2022 (2022).

30 Fox-Kemper, B. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte *et al.*) Ch. 9, 1211–1362 (Cambridge University Press, 2021).

31 Gulev, S. K. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate* (eds V. Masson-Delmotte *et al.*) Ch. 2, 287–422 (Cambridge University Press, 2021).

32 IPCC. in *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* (eds V. Masson-Delmotte *et al.*) Ch. AI, 541–562 (Cambridge University Press, 2018).

33 von Neumann, J. & Morgenstern, O. *Theory of games and economic behavior*. (Princeton University Press, 1944).

34 Drèze, J. H. & Modigliani, F. Consumption decisions under uncertainty. *Journal of Economic Theory* **5**, 308-335, doi:10.1016/0022-0531(72)90044-0 (1972).

35 Halsnæs, K. *et al.* in *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (eds B. Metz *et al.*) Ch. 2, 117–167 (Cambridge University Press, 2007).

36 Melvin, A. M. *et al.* Climate change damages to Alaska public infrastructure and the economics of proactive adaptation. *Proceedings of the National Academy of Sciences* **114**, E122-E131, doi:10.1073/pnas.1611056113 (2017).

37 Gasser, T. *et al.* Path-dependent reductions in CO2 emission budgets caused by permafrost carbon release. *Nature Geoscience* **11**, 830-835, doi:10.1038/s41561-018-0227-0 (2018).

38 Schubert, R. *et al. The Future Oceans: warming up, rising high, turning sour*. (WBGU (German Advisory Council on Global Change), 2006).

39 Gattuso, J.-P. *et al.* Contrasting futures for ocean and society from different anthropogenic CO2 emissions scenarios. *Science* **349**, aac4722, doi:10.1126/science.aac4722 (2015).

40 Bradley, R. & Drechsler, M. Types of Uncertainty. *Erkenntnis* **79**, 1225-1248, doi:10.1007/s10670-013-9518-4 (2014).

41 Dietrich, F. & Jabarian, B. Decision under normative uncertainty. *Economics and Philosophy* **38**, 372-394, doi:10.1017/S0266267121000201 (2022).

42 Rezai, A. & van der Ploeg, F. Climate policies under climate model uncertainty: Max-min and min-max regret. *Energy Economics* **68**, 4-16, doi:10.1016/j.eneco.2017.10.018 (2017).

43 Kelly, D. L. & Kolstad, C. D. Bayesian learning, growth, and pollution. *Journal of Economic Dynamics and Control* **23**, 491-518, doi:10.1016/S0165-1889(98)00034-7 (1999).

44 Lemoine, D. The Climate Risk Premium: How Uncertainty Affects the Social Cost of Carbon. *Journal of the Association of Environmental and Resource Economists* **8**, 27-57, doi:10.1086/710667 (2021).

45 van der Ploeg, F. & Rezai, A. The agnostic's response to climate deniers: Price carbon! *European Economic Review* **111**, 70-84, doi:10.1016/j.euroecorev.2018.08.010 (2019).
46 Schmidt, M. G. W., Lorenz, A., Held, H. & Kriegler, E. Climate targets under uncertainty: challenges and remedies. *Climatic Change* **104**, 783-791, doi:10.1007/s10584-010-9985-4 (2011).
47 Eyring, V. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate* (eds V. Masson-Delmotte *et al.*) Ch. 3, 423–552 (Cambridge University Press, 2021).
48 Emmerling, J. *et al.* The role of the discount rate for emission pathways and negative emissions. *Environmental Research Letters* **14**, 104008, doi:10.1088/1748-9326/ab3cc9 (2019).
49 Obersteiner, M. *et al.* How to spend a dwindling greenhouse gas budget. *Nature Climate Change* **8**, 7-10, doi:10.1038/s41558-017-0045-1 (2018).
50 Obersteiner, M. *et al.* Managing Climate Risk. *Science* **294**, 786-787, doi:10.1126/science.294.5543.786b (2001).
51 Schleussner, C.-F. *et al.* Overconfidence in climate overshoot. *Nature* **634**, 366-373, doi:10.1038/s41586-024-08020-9 (2024).
52 Rockström, J. *et al.* A safe operating space for humanity. *Nature* **461**, 472, doi:10.1038/461472a (2009).
53 Bednar, J., Obersteiner, M. & Wagner, F. On the financial viability of negative emissions. *Nature Communications* **10**, 1783, doi:10.1038/s41467-019-09782-x (2019).
54 Bednar, J. *et al.* Operationalizing the net-negative carbon economy. *Nature* **596**, 377-383, doi:10.1038/s41586-021-03723-9 (2021).
55 Geoffroy, O. *et al.* Transient Climate Response in a Two-Layer Energy-Balance Model. Part II: Representation of the Efficacy of Deep-Ocean Heat Uptake and Validation for CMIP5 AOGCMs. *Journal of Climate* **26**, 1859-1876, doi:10.1175/JCLI-D-12-00196.1 (2013).
56 Armour, K. C. Energy budget constraints on climate sensitivity in light of inconstant climate feedbacks. *Nature Climate Change* **7**, 331-335, doi:10.1038/nclimate3278 (2017).
57 Myhre, G. *et al.* in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds T.F. Stocker *et al.*) Ch. 8, 659–740 (Cambridge University Press, 2013).
58 Strassmann, K. M. & Joos, F. The Bern Simple Climate Model (BernSCM) v1.0: an extensible and fully documented open-source re-implementation of the Bern reduced-form model for global carbon cycle–climate simulations. *Geosci. Model Dev.* **11**, 1887-1908, doi:10.5194/gmd-11-1887-2018 (2018).
59 Gasser, T. *et al.* The compact Earth system model OSCAR v2.2: description and first results. *Geosci. Model Dev.* **10**, 271-319, doi:10.5194/gmd-10-271-2017 (2017).
60 He, Y. *et al.* Radiocarbon constraints imply reduced carbon uptake by soils during the 21st century. *Science* **353**, 1419-1424, doi:10.1126/science.aad4273 (2016).
61 Goodwin, P., Haigh, I. D., Rohling, E. J. & Slangen, A. A new approach to projecting 21st century sea-level changes and extremes. *Earth's Future* **5**, 240-253, doi:10.1002/2016EF000508 (2017).
62 Mengel, M. *et al.* Future sea level rise constrained by observations and long-term commitment. *Proceedings of the National Academy of Sciences* **113**, 2597-2602, doi:10.1073/pnas.1500515113 (2016).
63 Bernie, D., Lowe, J., Tyrrell, T. & Legge, O. Influence of mitigation policy on ocean acidification. *Geophysical Research Letters* **37**, L15704, doi:10.1029/2010GL043181 (2010).
64 Ricciuto, D. M., Davis, K. J. & Keller, K. A Bayesian calibration of a simple carbon cycle model: The role of observations in estimating and reducing uncertainty. *Global Biogeochemical Cycles* **22**, doi:10.1029/2006GB002908 (2008).
65 Bayes, T. & Price, R. LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, F. R. S. communicated by Mr. Price, in a letter to John Canton, A. M. F. R. S. *Philosophical Transactions of the Royal Society of London* **53**, 370-418, doi:10.1098/rstl.1763.0053 (1763).
66 Salvatier, J., Wiecki, T. V. & Fonnesbeck, C. Probabilistic programming in Python using PyMC3. *PeerJ Computer Science* **2**, e55, doi:10.7717/peerj-cs.55 (2016).
67 Kucukelbir, A., Tran, D., Ranganath, R., Gelman, A. & Blei, D. M. Automatic Differentiation Variational Inference. *Journal of Machine Learning Research* **18**, 1-45 (2017).

68 Smith, C. *et al.* in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte *et al.*) Ch. 7.SM, (2021).
69 Le Quéré, C. *et al.* Global Carbon Budget 2018. *Earth Syst. Sci. Data* **10**, 2141-2194, doi:10.5194/essd-10-2141-2018 (2018).
70 Gasser, T. *et al.* Historical CO2 emissions from land use and land cover change and their uncertainty. *Biogeosciences* **17**, 4075-4101, doi:10.5194/bg-17-4075-2020 (2020).
71 Smith, T. M., Reynolds, R. W., Peterson, T. C. & Lawrimore, J. Improvements to NOAA's Historical Merged Land–Ocean Surface Temperature Analysis (1880–2006). *Journal of Climate* **21**, 2283-2296, doi:10.1175/2007JCLI2100.1 (2008).
72 Hansen, J., Ruedy, R., Sato, M. & Lo, K. GLOBAL SURFACE TEMPERATURE CHANGE. *Reviews of Geophysics* **48**, doi:10.1029/2010RG000345 (2010).
73 Morice, C. P., Kennedy, J. J., Rayner, N. A. & Jones, P. D. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *Journal of Geophysical Research: Atmospheres* **117**, doi:10.1029/2011JD017187 (2012).
74 Cowtan, K. & Way, R. G. Coverage bias in the HadCRUT4 temperature series and its impact on recent temperature trends. *Quarterly Journal of the Royal Meteorological Society* **140**, 1935-1944, doi:10.1002/qj.2297 (2013).
75 Rohde, R. *et al.* Berkeley Earth Temperature Averaging Process. *Geoinformatics & Geostatistics: An Overview* **1**, doi:10.4172/gigs.1000103 (2013).
76 Roe, G. H. & Baker, M. B. Why Is Climate Sensitivity So Unpredictable? *Science* **318**, 629-632, doi:10.1126/science.1144735 (2007).
77 Dlugokencky, E. & Tans, P. *Trends in Atmospheric Carbon Dioxide*, <https://gml.noaa.gov/ccgg/trends/global.html> (2021).
78 Zhao, M., Heinsch, F. A., Nemani, R. R. & Running, S. W. Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment* **95**, 164-176, doi:10.1016/j.rse.2004.12.011 (2005).
79 Ciais, P. *et al.* in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds T.F. Stocker *et al.*) Ch. 6, 465–570 (Cambridge University Press, 2013).
80 Yu, Z., Loisel, J., Brosseau, D. P., Beilman, D. W. & Hunt, S. J. Global peatland dynamics since the Last Glacial Maximum. *Geophysical Research Letters* **37**, doi:10.1029/2010GL043584 (2010).
81 Parkes, D. & Marzeion, B. Twentieth-century contribution to sea-level rise from uncharted glaciers. *Nature* **563**, 551-554, doi:10.1038/s41586-018-0687-9 (2018).
82 Slangen, A. B. A. *et al.* Anthropogenic forcing dominates global mean sea-level rise since 1970. *Nature Climate Change* **6**, 701-705, doi:10.1038/nclimate2991 (2016).
83 Howard, P. H. & Sterner, T. Few and Not So Far Between: A Meta-analysis of Climate Damage Estimates. *Environmental and Resource Economics* **68**, 197-225, doi:10.1007/s10640-017-0166-z (2017).
84 Drupp, M. A., Freeman, M. C., Groom, B. & Nesje, F. Discounting Disentangled. *American Economic Journal: Economic Policy* **10**, 109-134, doi:10.1257/pol.20160240 (2018).
85 Cobb, C. W. & Douglas, P. H. A Theory of Production. *The American Economic Review* **18**, 139-165 (1928).
86 Friedlingstein, P. *et al.* Global Carbon Budget 2020. *Earth Syst. Sci. Data* **12**, 3269-3340, doi:10.5194/essd-12-3269-2020 (2020).
87 Riahi, K. *et al.* The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change* **42**, 153-168, doi:10.1016/j.gloenvcha.2016.05.009 (2017).
88 Gasser, T., Ciais, P. & Lewis, S. L. How the Glasgow Declaration on Forests can help keep alive the 1.5°C target. *Proceedings of the National Academy of Sciences* **119**, e2200519119, doi:10.1073/pnas.2200519119 (2022).
89 Rogelj, J., McCollum, D. L., Reisinger, A., Meinshausen, M. & Riahi, K. Probabilistic cost estimates for climate change mitigation. *Nature* **493**, 79-83, doi:10.1038/nature11787 (2013).
90 Shapiro, A. in *Lectures on Stochastic Programming* (eds Alexander Shapiro, Darinka Dentcheva, & Andrzej Ruszczynski) Ch. 5, 155-252 (Society for Industrial and Applied Mathematics, 2009).

91 Cheritel, C. Results for Thomas Gasser, Armon Rezai, Côme Cheritel, Artem Baklanov, and Michael Obersteiner, "Negative emissions to mitigate Earth system risks.". doi:10.5281/zenodo.18461481 (2026).

92 Gasser, T. Pathfinder v1.0.1. doi:10.5281/zenodo.7194161 (2022).

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Author contributions

TG, AR, CC, AB, MO designed the study and experiments. TG designed the original Pathfinder model. AB and AR implemented two successive versions of the optimisation setup; CC adjusted and ran the final version and additional sensitivity tests. TG led the writing of the manuscript.

Competing interests

The authors declare no competing interests.

Table 1. Key attributes of the optimal climate strategies resulting from ex-post and ex-ante approaches.

	Peak GSAT (°C)	Short-term emission budget[a] (GtCO2)	Year of net zero CO2 emission[b]	Long-term emission budget[c] (GtCO2)	Carbon price in 2030[d] (USD tCO2^{-1})
Cost-benefit analysis (CBA)					
Ex-post	1.6 (1.4, 1.8)	740 (440, 1160)	2064 (2049, 2079)	-2970 (-3530, -2370)	250 (182, 344)
	1.6 ± 0.1	750 ± 220	2064 ± 9	-2970 ± 360	257 ± 52
Ex-ante	1.5 (1.3, 1.7)	360 (310, 420)	2041	-2950 (-3020, -2840)	425
	1.5 ± 0.1	360 ± 30	2041	-2940 ± 60	425
Cost-effective 2°C target					
Ex-post	2.0	1870 (840, >3660)	2114 (2064, >2500)	1470 (120, 3490)	104 (47, 219)
Ex-ante (50%)[e]	2.0 (1.6, 2.7)	1670 (1610, 1740)	2111	-80 (-130, -10)	112
Ex-ante (95%)[e]	1.6 (1.4, 2.0)	680 (620, 740)	2059	-980 (-1030, -910)	241
Cost-effective 1.5°C target[f]					
Ex-post	1.5	930 (470, >2110)	2117 (2048, >2500)	0 (-120, 1750)	241 (112, 352)
Ex-ante (50%)[e]	1.5 (1.3, 1.9)	470 (420, 540)	2082	-1040 (-1090, -970)	395

Median value with 90% confidence interval in parentheses, also reported as mean ± standard deviation for the CBA. GtCO2 is giga-tonne of CO2.

[a] Defined as cumulative CO2 emissions from 2015 to the year of net zero, or displayed with a > sign if emissions do not enter the negative domain.

[b] Displayed with a > sign if emissions do not enter the negative domain. Uncertainty ranges lower than or equal to ±1 year are not shown.

[c] Defined as cumulative CO2 emissions from 2015 to 2500.

[d] All prices in this study are constant 2015 United States Dollars (USD).

[e] Confidence level with which the target is met.

[f] Meeting 1.5 °C with 95% confidence is unfeasible according to our model (Supplementary Table 2).

Figure 1. Conceptual diagram summarizing the ex-post and ex-ante approaches used in this study. SCM: simple climate model; CMIP6: coupled model intercomparison project phase 6; IPCC: intergovernmental panel on climate change; AR6: sixth assessment report; GCB: global carbon budget; SOW: state of the world; CBA: cost-benefit analysis.

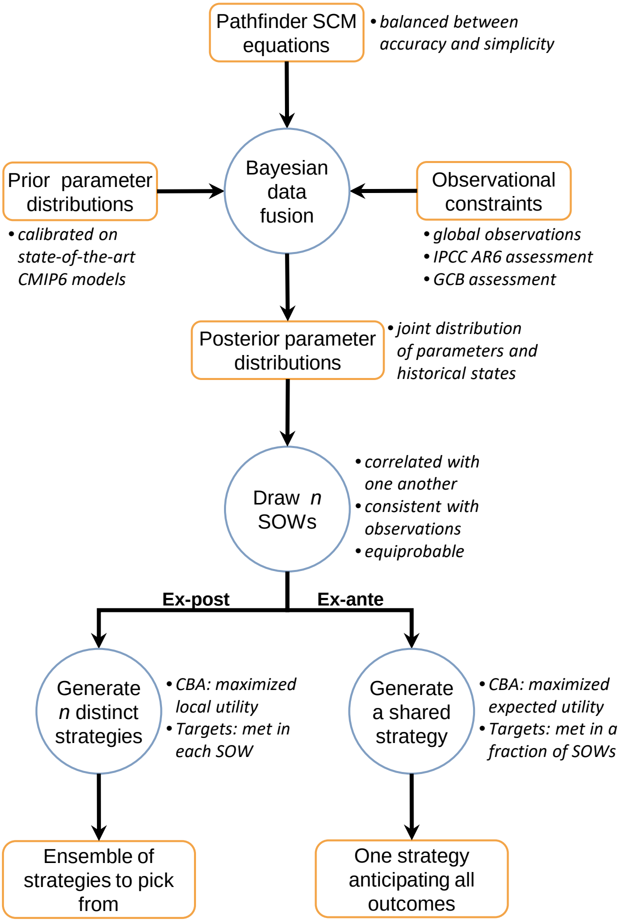
Figure 2. Time series and confidence interval of global surface air temperature (GSAT) change, anthropogenic CO2 emissions, and carbon prices. (a, b, c) GSAT change with respect to the preindustrial period. **(d, e, f)** Anthropogenic CO2 emissions. **(g, h, i)** Carbon price, reported as the social cost of carbon (SCC) calculated as the ratio of the weighted Lagrange multipliers (Methods) for the cost-benefit analysis (CBA). **(a, d, g)** Time series in the CBA. **(b, e, h)** Time series in the cost-effective 2 °C target experiments. **(c, f, i)** Time series in the cost-effective 1.5 °C target experiments. Only the 50% confidence level for the ex-ante approach is shown for the cost-effective experiments, for readability. Dark and light plain lines are the median of the ensemble from the ex-post or ex-ante approaches, respectively. Light dotted or dark plain shaded areas are the corresponding 90% uncertainty (i.e. 5^{th} to 95^{th} percentiles) range (n=600), respectively. Note that in the ex-ante approach the carbon price has no uncertainty, and the anthropogenic emissions very little and only at the start of the simulation, whereas GSAT change has no uncertainty after reaching the target in the cost-effective ex-post approach. Note also that these confidence intervals do not describe the probability that the true optimal pathway lies in that range. All prices in this study are constant 2015 United States Dollars (USD). GtCO2 is giga-tonne of CO2.

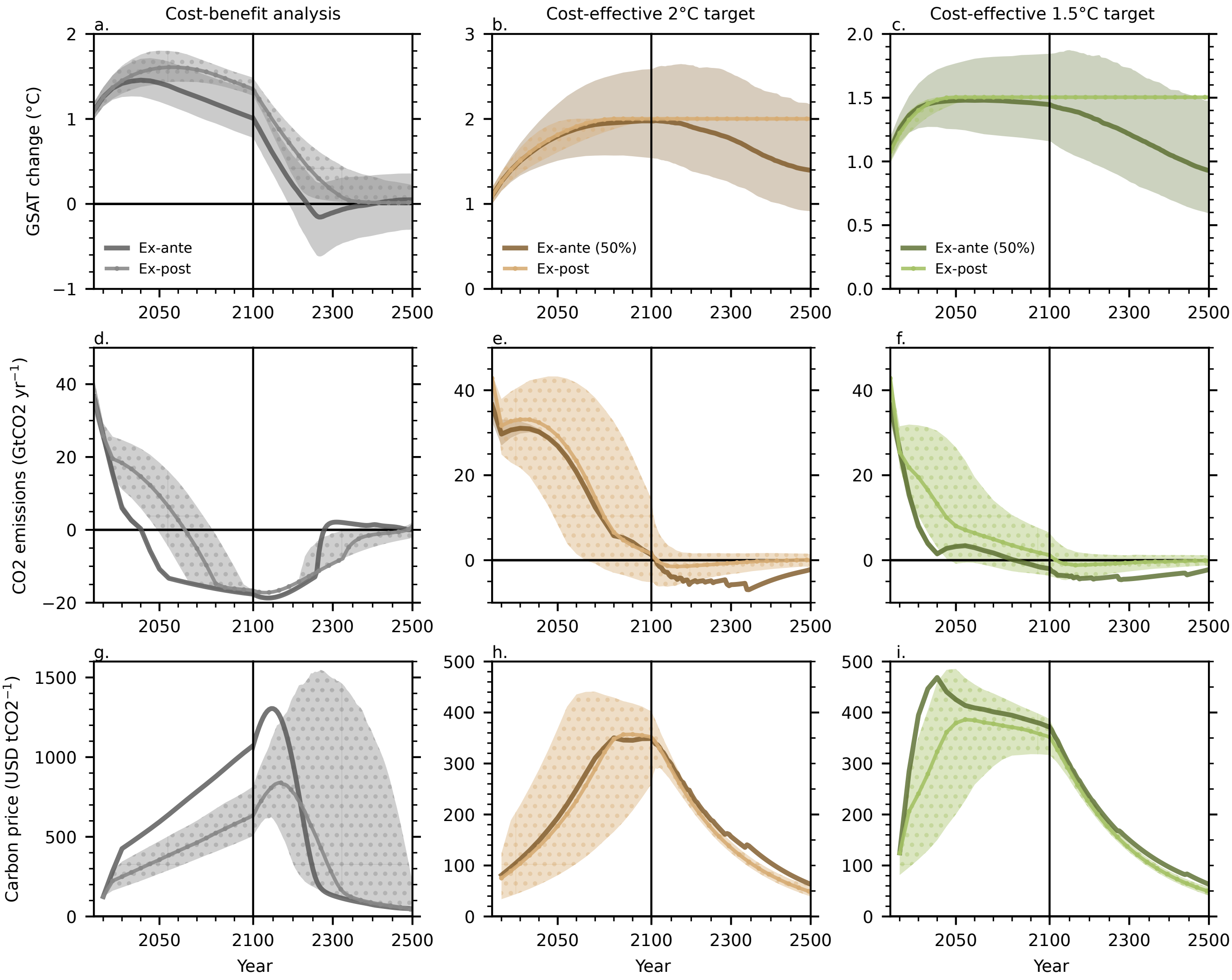
Figure 3. Change in key attributes of the optimal climate strategies from the ex-ante approach relative to the ex-post approach. (a) Change in short-term emission budgets (positive values indicate a reduction). **(b)** Change in year of net zero CO_2 emissions (positive values indicate earlier net zero). **(c)** Change in long-term cumulative net-negative CO_2 emissions (positive values indicate an increase in carbon capture). **(d)** Change in carbon price in 2030. Markers and colours show the cost-benefit analysis or cost-effective experiments for different targets: global warming, thawed fraction of permafrost carbon (PFC), surface ocean acidification (in pH unit), and sea-level rise (SLR) decadal speed. For cost-effective experiments, the *x*-axis shows the levels of confidence in reaching the target. For the cost-benefit analysis (CBA), the ex-ante approach leads to a unique value that is compared to the mean of the ensemble from the ex-post approach. Short-term CO_2 budgets and years of net zero emission are not shown for experiments that do not require negative emissions. Note the semi-logarithmic scale on the *y*-axis in all panels. All prices in this study are constant 2015 United States Dollars (USD). $GtCO_2$ is giga-tonne of CO_2.

Figure 4. Cumulative probability distributions of carbon prices in 2030. (a) Cost-benefit analysis (CBA). **(b-h)** Earth system targets . The continuous line is the distribution of carbon prices in the ensemble of strategies from the ex-post approach. Markers are the carbon prices from the ex-ante approach, for the corresponding level of confidence shown on the *y*-axis. CBA with the ex-ante approach provides a unique carbon price that is reported as a vertical dashed line that can be compared with the mean of the ensemble from the ex-post approach reported as a vertical thin line. We define the carbon price premium as the horizontal distance between the ex-post line and the ex-ante markers for cost-effective setups, and between both vertical lines for CBA. All prices in this study are constant 2015 United States Dollars (USD).

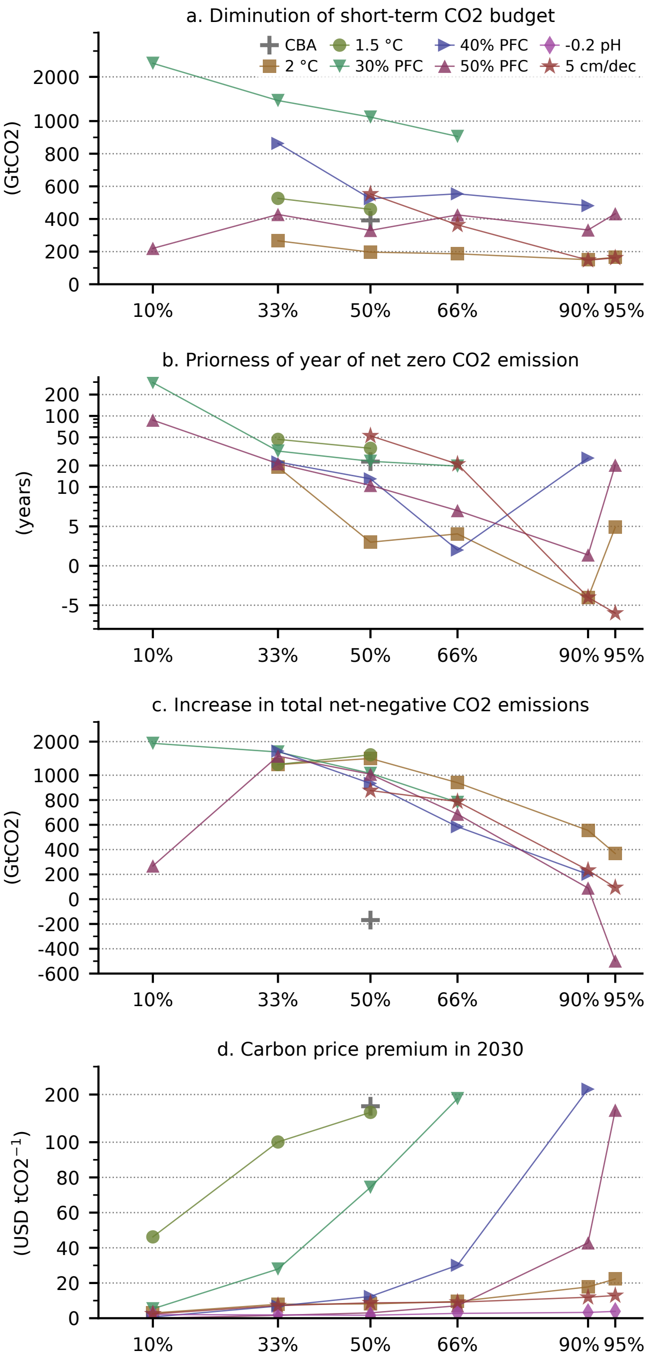
Editorial Summary:
This study develops ex-ante climate strategies that anticipate Earth system uncertainty. Compared with ex-post ones, they adopt precautionary measures to mitigate risks: earlier net-zero emission, higher carbon price, and long-term carbon capture.

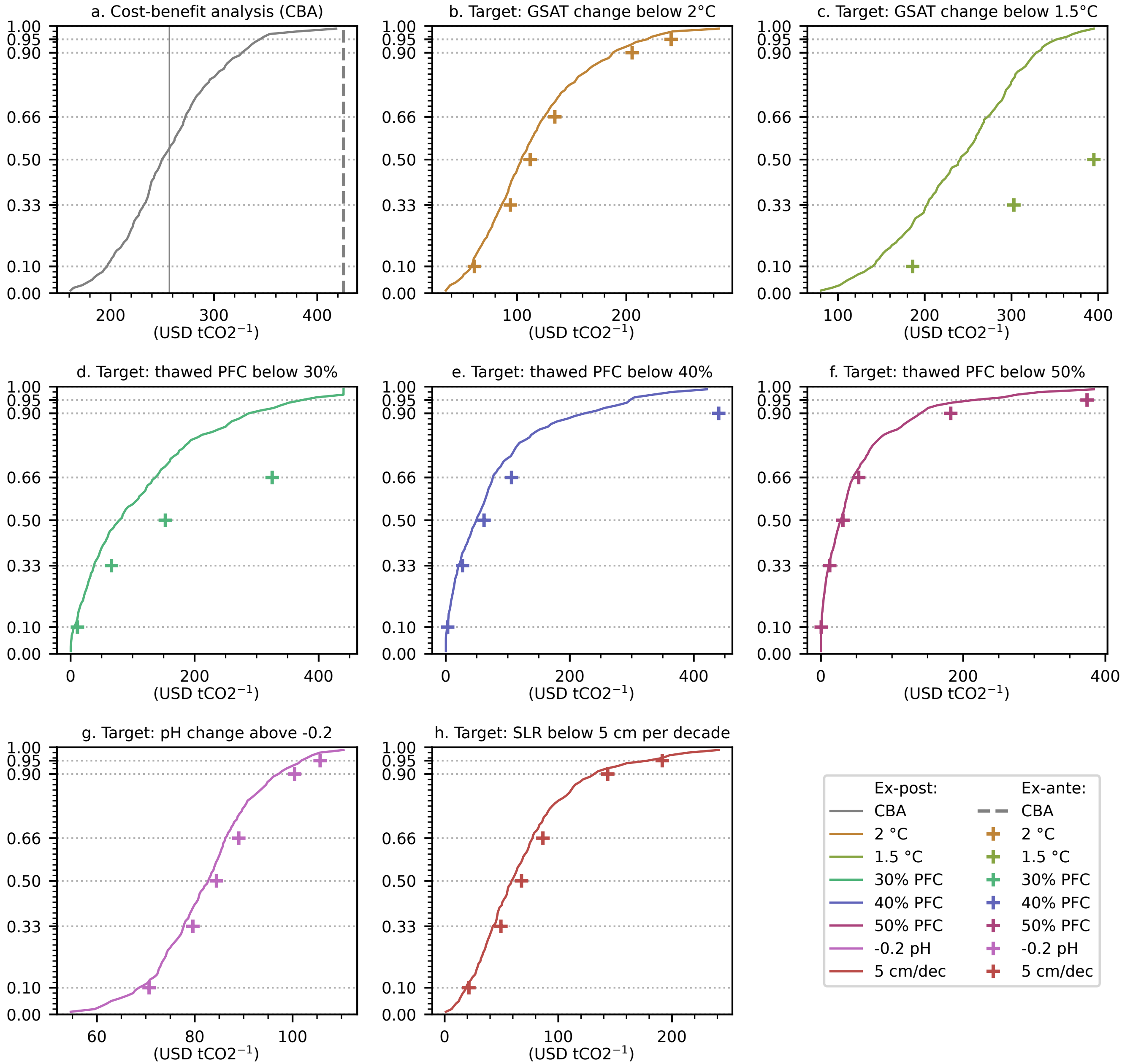
Peer Review Information: *Nature Communications* thanks Jacob Wessel, Saeed Moghayer and the other anonymous, reviewer(s) for their contribution to the peer review of this work. A peer review file is available."


Pathfinder SCM equations
• balanced between accuracy and simplicity
Prior parameter distributions
• calibrated on state-of-the-art CMIP6 models
Bayesian data fusion
Observational constraints
• global observations
• IPCC AR6 assessment
• GCB assessment
Posterior parameter distributions
• joint distribution of parameters and historical states
Draw n SOWs
• correlated with one another
• consistent with observations
• equiprobable
Ex-post
Ex-ante
Generate n distinct strategies
• CBA: maximized local utility
• Targets: met in each SOW
Generate a shared strategy
• CBA: maximized expected utility
• Targets: met in a fraction of SOWs
Ensemble of strategies to pick from
One strategy anticipating all outcomes



Cost-benefit analysis
Cost-effective 2°C target
Cost-effective 1.5°C target
a.
b.
c.
d.
e.
f.
g.
h.
i.
GSAT change (°C)
CO2 emissions (GtCO2 yr^{-1})
Carbon price (USD tCO2^{-1})
Ex-ante
Ex-post
Ex-ante (50%)
Ex-post
Ex-ante (50%)
Ex-post
2050
2100
2300
2500
Year


a. Diminution of short-term CO2 budget
CBA
1.5 °C
40% PFC
-0.2 pH
2 °C
30% PFC
50% PFC
5 cm/dec
(GtCO2)
2000
1000
800
600
400
200
0
10%
33%
50%
66%
90%
95%
b. Priorness of year of net zero CO2 emission
(years)
200
100
50
20
10
5
0
-5
c. Increase in total net-negative CO2 emissions
(GtCO2)
-200
-400
-600
d. Carbon price premium in 2030
(USD tCO2^{-1})
80
60
40


a. Cost-benefit analysis (CBA)
b. Target: GSAT change below 2°C
c. Target: GSAT change below 1.5°C
d. Target: thawed PFC below 30%
e. Target: thawed PFC below 40%
f. Target: thawed PFC below 50%
g. Target: pH change above -0.2
h. Target: SLR below 5 cm per decade
1.00
0.95
0.90
0.66
0.50
0.33
0.10
0.00
(USD tCO2^{-1})
Ex-post:
Ex-ante:
CBA
2 °C
1.5 °C
30% PFC
40% PFC
50% PFC
-0.2 pH
5 cm/dec