MACROM: An Optimal Control Model for Balancing Climate Change Abatement and Damage Trade-offs

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Abstract

The current pace of global emissions reduction is inadequate to meet the Paris Agreement temperature target of 1.5°C. While carbon dioxide removal (CDR) is increasingly viewed as necessary to meet these targets, questions remain about the optimal scale and timing of deployment when both costs and climate damages are considered. Here we present MACROM, an optimal control climate-economic model that identifies cost-optimal pathways for deploying emissions reduction and CDR to achieve the 1.5°C target by 2100. MACROM minimises the combined costs of climate action and temperature-related economic damages, while targeting a specific temperature goal and year. We examine cost-optimal pathways across five Shared Socioeconomic Pathways, finding that immediate, large-scale deployment of both emissions reduction and CDR minimises costs across all scenarios. Optimal solutions require 492-1,894 $GtCO_2$ of emissions reduction and 394-1,374 $GtCO_2$ of CDR by 2100, with CDR volumes well beyond current feasibility estimates. Temperature-related damages comprise 66-90% of total costs, far exceeding abatement expenditure. Sensitivity analysis reveals that discount rate and economic damage coefficients are the primary drivers of cost variability, while CDR and emissions reduction costs exert minimal influence. Our results demonstrate that even with unlimited CDR capacity, immediate emissions reduction remains essential for cost-effective climate action to achieve the Paris Agreement target this century.

Keywords

optimal control, carbon dioxide removal, emissions reduction, climate-economic modelling, Paris Agreement

1. Introduction

Global mean temperature is projected to increase by 2.3-2.8°C above pre-industrial levels this century (UNEP, 2025). With 195 countries as signatories, the Paris Agreement target to "pursue efforts to limit the temperature increase to 1.5°C" (UNFCCC, 2015) has guided climate abatement policy over the past decade. Yet the inadequate pace of climate action to date (Lamb *et al.*, 2024; UNEP, 2025) makes it likely that the 1.5°C target will be exceeded within the next decade (Reisinger and Geden, 2023; Bevacqua, Schleussner and Zscheischler, 2025). Consequently, strategies to achieve the Paris Agreement target increasingly require the use of large-scale carbon dioxide removal (CDR) to extract historical emissions from the atmosphere, and to offset future emissions from hard-to-abate industries and existing fossil fuel infrastructure (Hilaire *et al.*, 2019; Martin *et al.*, 2021; Schleussner *et al.*, 2024; Reisinger *et al.*, 2025; UNEP, 2025).

One potential approach to achieve the Paris Agreement target is to allow a temporary overshoot of a temperature threshold before warming is reversed (Carton *et al.*, 2023; Schleussner *et al.*, 2024). CDR decouples temperature stabilisation from gross anthropogenic CO_2 emissions by removing excess emissions in the future. However, the economic ramifications of this strategy warrant scrutiny. Even assuming CDR can be deployed at the necessary scale, delaying emissions mitigation and allowing a temporary temperature overshoot may be a more expensive strategy to achieve temperature targets than near-term emissions reduction, when accounting for both deployment costs and temperature-related damage over the entire time horizon (Akimoto, Sano and Tomoda, 2018; Riahi *et al.*, 2021). Early use of both emissions reduction and CDR reduces temperature-related damages in the long-term but necessitates expensive technology. In contrast, delayed deployment of emissions reduction and CDR increases damages, while potentially reducing climate abatement costs as technology costs decrease.

Identifying cost-optimal abatement pathways to meet a temperature target requires minimising the combined total costs of climate change action (via emissions reduction and CDR expenditure) and climate inaction (e.g. through temperature-related damage to gross world product (GWP)) (Orlov *et al.*, 2020) across the entire time horizon. Existing approaches, primarily Integrated Assessment Models (IAMs), employ two main methodologies to quantify abatement pathways: cost-benefit and cost-minimisation analysis. Cost-benefit IAMs balance avoided economic damages and the reduced economic consumption associated with abatement expenditure (Kellett *et al.*, 2019). This means that these models trade-off climate action against other economic priorities and opportunity costs (Botzen and van den Bergh, 2014), concluding that temperature stabilisation above 1.5°C can be optimal (Hänsel *et al.*, 2020). In contrast, cost-minimisation IAMs, which were used extensively in the IPCC *Special Report on 1.5°C* (2018), minimise only abatement expenditure in targeting a specified radiative forcing level, without accounting for climate-related damages (IPCC, 2018).

Here we present the Mitigation and Carbon Removal Optimisation Model (MACROM), a simple, emissions-driven, cost-minimisation climate-economic model to project cost-optimal deployment of mitigation and CDR to achieve a specific temperature target. MACROM captures 1) the trade-offs between the costs of climate action and the economic damages of climate inaction and 2) the optimal timing and scale of deploying climate action across the target's time horizon. We use MACROM to assess the mitigation and CDR required to return temperature to the Paris Agreement 1.5°C by 2100 across different socio-economic futures.

MACROM uses optimal control theory (Lenhart and Workman, 2007), a mathematical framework for identifying the optimal way to operate a dynamic system, balancing trade-offs over time to achieve a desired system state at minimum cost or maximum reward (Lenhart and Workman, 2007). Optimal control has previously been used in climate-economic modelling to explore optimal pathways to achieve welfare maximisation (Bahn, Haurie and Malhamé, 2008; Nordhaus, 2014; Maurer and Semmler, 2015; Atolia *et al.*, 2018; Moreno-Cruz, Wagner and Keith, 2018; Dietz and Venmans, 2019; Kellett *et al.*, 2019), cost or emissions minimisation (Soldatenko and Yusupov, 2018; Verma *et al.*, 2024), sustainability maximisation (Doshi *et al.*, 2015; Nisal *et al.*, 2022), social welfare and temperature deviation (Heris and Rahnamayan, 2020) or abatement and damage costs (Cerasoli and Porporato, 2023). Optimal control is well suited to identifying the best way to control a dynamic system over time (Lenhart and Workman, 2007), as unlike static optimisation approaches, it can simultaneously balance multiple objectives and constraints across different time horizons (Liberzon, 2012).

MACROM simulates the change in cumulative CO_2 emissions over time resulting from anthropogenic activity, as well as reductions in CO_2 emissions brought about by mitigation (stopping emissions from being released) and CDR (removing emissions from the atmosphere). Here, we assume no constraints on the availability of mitigation or CDR controls, allowing us to explore the demand for emissions mitigation, even when CDR faces no barriers to deployment. In contrast with approaches that prescribe abatement actions and timing based on realistic deployment constraints, this approach enables exploration of pathways that combine mitigation and CDR optimally, even when the required deployment capacities are infeasible given current assumptions about future technology development (Strefler *et al.*, 2018; Hilaire *et al.*, 2019; Rogelj *et al.*, 2019; Ganti *et al.*, 2024). The aim of MACROM is to reveal insights about the influence of deployment costs and temperature-related damages on optimal pathways to achieve temperature targets, such as the Paris Agreement, rather than providing quantitative recommendations.

Using MACROM, we first identify the optimal deployment of mitigation and CDR across a range of Shared Socioeconomic Pathways (SSPs) to achieve the Paris Agreement target of limiting warming to 1.5°C by 2100. We then conduct a sensitivity analysis to investigate key parameters driving the volume of mitigation and CDR deployed, and the total costs. We specifically investigate the role of global temperature sensitivity to CO_2 emissions, along with economic factors such as future discount rates and the cost of deploying abatement controls. Finally, we examine how further delays to climate action affect optimal deployment of mitigation and CDR and the resulting total costs. We show that, even with unlimited CDR capacity, immediate and large-scale deployment of both mitigation and CDR is the most cost-effective approach to achieving 1.5°C by 2100.

2. Methods.

Our methods are organised as follows. Section 2.1 introduces the equations for the evolution of cumulative CO_2 emissions and temperature response to the control variables, and links these to a damage model, while Section 2.2 formulates the optimal control problem. Section 2.3 outlines the approach of the model sensitivity analysis and Section 2.4 describes how the model implements delayed deployment of abatement solutions.

2.1 Model of cumulative emissions and costs

MACROM models cumulative CO_2 emissions, $c(t)$ ($GtCO_2$), as its state variable, while $u_m(t)$ and $u_r(t)$ are control variables representing mitigation ($GtCO_2$) and CDR ($GtCO_2$) respectively. The state variable cannot be adjusted directly, however by changing the use of the control variables over time, the state can be controlled (Liberzon, 2012). The evolution of cumulative CO_2 emissions is represented as

$$\frac{dc}{dt} = E(t) - u_m(t) - u_r(t). \tag{E1}$$

To maintain simplicity, MACROM uses Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathways (SSPs) forecasts of CO_2 emissions as the exogenous input $E(t)$ (Fig S1). This is the SSP-baseline yearly emissions forecast in the absence of mitigation or CDR. Emissions forecasts are given by the five baseline SSPs independently developed for the IPCC Sixth Assessment Report (Masson-Delmotte *et al.*, 2021). These pathways describe different socio-economic futures, including predictions of population and economic growth, fossil fuel usage and land-use changes (Riahi *et al.*, 2017). The baseline emissions scenarios within these pathways do not include assumptions of explicit climate abatement policies; however, they do develop an energy-mix assumption, based on the socio-economic futures envisaged. SSP1 and SSP4 assume a decrease in fossil fuel energy consumption, while SSP3 and SSP5 assume an increase in fossil fuel usage. SSP2 reflects a society whose energy consumption pattern is not markedly different from the present. Using baseline emissions forecasts allows a comparison of climate action required to achieve the Paris Agreement under different possible futures. Emissions forecast data was sourced from Riahi *et al.,* (2017).

In (E1) mitigation refers to any natural or technological process that prevents CO_2 emissions from being released into the atmosphere. CDR refers to any natural or technological process that removes CO_2 emissions from the atmosphere after being released (for example, afforestation/reforestation or direct air capture), and which is additional to current environmental carbon sinks. All CDR is assumed to be permanent storage, in line with standard climate-economic model assumptions (Brunner, Hausfather and Knutti, 2024).

Cumulative CO_2 emissions are converted to a temperature anomaly (°C, compared to the preindustrial period),

$$T(t) = T_0 + \gamma c(t), \tag{E2}$$

where T_0 is the temperature anomaly at the start of the simulation period compared to the pre-industrial average (here set to 1.2°C) and γ is the transient climate response to cumulative carbon emissions (TCRE, °C/MtCO_2). The TCRE is the expected amount of global warming that occurs with an increase in CO_2 in the atmosphere (Masson-Delmotte *et al.*, 2021). This linear relationship is appropriate as, to a first approximation, global mean surface temperature linearly increases with cumulative emissions at the magnitudes being considered here (Moreno-Cruz, Wagner and Keith, 2018).

We assume an increasing marginal unit cost of mitigation and CDR, reflecting the expectation that the cost of climate interventions becomes progressively more expensive for every additional GtCO_2. This approach assumes that early solutions will comprise low-cost efficiency improvements, while later abatement necessitates more expensive, or novel intervention solutions (Edelenbosch *et al.*, 2024; Lamb *et al.*, 2024). Additionally, increasing costs with deployment accounts for limitations on the resources available to support land-based storage solutions (Boysen *et al.*, 2017; Gidden *et al.*, 2025). This increasing cost structure is consistent with the implementation in IAMs, such as DICE (Nordhaus, 2014), where marginal costs increase convexly.

Separate marginal cost curves for mitigation and CDR are defined using a second-order polynomial

$$MC_m(x) = \alpha x^2 + \beta x,$$

where x represents the cumulative quantity of CO_2 (in GtCO_2) either mitigated or removed, and $MC(x)$ is the marginal cost (in trillion USD per GtCO_2) of abating the x-th unit. The function is constrained to pass through the origin, such that $MC(0) = 0$. The parameters α and β are determined using two calibration points: the 1st GtCO_2 mitigated/removed and the 50th GtCO_2 mitigated/removed. For example, the total cost F_m of mitigating u_m GtCO_2 is

$$F_m(u_m) = \int_0^{u_m} \alpha x^2 + \beta x \, \mathrm{d}x = \frac{\alpha}{3} {u_m}^3 + \frac{\beta}{2} {u_m}^2,$$

where the closed-form solution is obtained by evaluating the definite integral. Similarly, for CDR, we define the marginal cost curve $MC_r(x) = \kappa x^2 + \rho x,$ where κ and ρ are determined using calibration points for CDR costs analogous to those used for mitigation. Values for the calibration points for mitigation and CDR marginal cost curves are derived from the literature (See Section S1, S2).

We restrict our consideration of economic impacts to direct climate change-related expenditure, formulated as 1) the cost to implement abatement solutions and 2) loss of Gross World Product (GWP) caused by rising temperatures. This is in contrast to cost-benefit IAM approaches, where opportunity costs and social utility are optimised, or cost-minimisation IAMs, where economic damage from warming is not considered alongside abatement costs (Ackerman *et al.*, 2009; Botzen and van den Bergh, 2014; IPCC, 2018).

Cumulative costs and damages (J) are therefore given by

$$J = \int_{t_0}^{t_f} [F_m(u_m) + F_r(u_r) + bT(t)^2] e^{-\delta(t-t_0)}\,\mathrm{d}t. \tag{E3}$$

The first two terms of the integrand are explained above. The third term of the integrand, $b(T(t))^2$, calculates the residual climate damage caused by any temperature increase above the preindustrial period (E2), where b is the economic damage coefficient representing the decrease of economic activity from warming. This damage function depends directly on the temperature anomaly, and is formulated as a quadratic as damages are expected to increase non-linearly with temperature increase (Nordhaus, 2008). Finally, δ is the constant social discount rate used to convert future costs and economic benefits to present-value terms. The exponential term applies time-discounting such that costs and benefits occurring further in the future are valued less in today's terms, consistent with standard economic practice (Arrow *et al.*, 2013). We simulate from $t_0 = 2020$ to $t_f = 2100$.

2.2 Solving the optimal control problem

We solve the optimal control problem using Pontryagin's Maximum Principle (PMP), deriving necessary conditions that are solved in continuous time (Kopp, 1962). Our formulation presupposes a global commitment among policymakers to achieve the Paris Agreement target of limiting warming to 1.5°C by 2100. PMP finds a single optimal solution by minimising (E3), subject to the temperature constraint and the system dynamics (E1). The resulting optimal control pathways reveal the scope and timing of abatement required.

This is formulated as

$$\min_{u_m(t), u_r(t)} J = \int_{t_0}^{t_f} [F_m(u_m) + F_r(u_r) + b(T(t))^2] e^{-\delta(t-t_0)}\,dt, \tag{E4}$$

$$s.t. \qquad \frac{dc}{dt} = E(t) - u_m(t) - u_r(t), \tag{E1}$$

$$c(t_0) = c_0, \tag{E5}$$

$$c(t_f) = 650, \tag{E6}$$

$$0 \leq u_m(t) < E(t);\ \forall t, \tag{E7}$$

$$u_r(t) \geq 0. \tag{E8}$$

For all scenarios, cumulative emissions at the starting time, $c(t_0)$, are set to zero. The 1.5°C temperature constraint is converted to cumulative emissions using (E2), resulting in a cumulative emissions target of 650 $GtCO_2$ in 2100 (E6). The control variables are non-negative, with mitigation capped by annual emissions $E(t)$.

We apply PMP to (E4) to derive the Hamiltonian, introducing an adjoint variable $\lambda = \lambda(t)$, which is the co-state variable associated with (E1)

$$\mathcal{H} = [F_m(u_m) + F_r(u_r) + b(T(t))^2]e^{-\delta(t-t_0)} + \lambda[E(t) - u_m(t) - u_r(t)]. \tag{E9}$$

We interpret $\lambda(t)$ as the marginal cost to J of adding one more unit of CO_2 into the atmosphere at time t. In contrast to standard optimal control problems that fix the co-state variable at the final time, we fix the state variable instead, resulting in a two-point boundary value problem with conditions on $c(t)$ at both the start and end times (E5, E6) (Hartl, Sethi and Vickson, 1995; Lenhart and Workman, 2007). The problem is well-defined for minimisation, since the second derivative of (E9) is positive in the control variables (Cerasoli and Porporato, 2023).

To incorporate the lower bounds of (E7) and (E8), we apply the Karush-Kuhn-Tucker (KKT) conditions (Liberzon, 2012) to construct the Lagrangian in the form $\mathcal{L}\big(t, c(t), u(t), \lambda(t)\big)$,

$$\mathcal{L} = \mathcal{H} + \mu_1(t)u_m(t) + \mu_2(t)u_r(t), \tag{E10}$$

where μ_1 and μ_2 are the Lagrangian multipliers for mitigation and CDR respectively, that ensure the lower bound constraints are satisfied. Since the upper bound constraint on $u_m(t)$ is a strict inequality, it does not have an associated Lagrange multiplier (Liberzon, 2012).

The necessary conditions for an optimal solution are obtained by finding the partial derivative of the control variables in (E10)

$$\frac{\partial \mathcal{L}}{\partial u_m} = (\alpha {u_m}^2 + \beta u_m)e^{-\delta(t-t_0)} - \lambda + \mu_1 = 0, \tag{E11}$$

$$\frac{\partial \mathcal{L}}{\partial u_r} = (\kappa {u_r}^2 + \rho u_r)e^{-\delta(t-t_0)} - \lambda + \mu_2 = 0, \tag{E12}$$

and the complementary slackness conditions

$$\mu_1 \geq 0, u_m \geq 0, \mu_1 u_m = 0, \tag{E13}$$

$$\mu_2 \geq 0, u_r \geq 0, \mu_2 u_r = 0. \tag{E14}$$

(E13) and (E14) prevent non-physical solutions of negative mitigation and CDR (Liberzon, 2012).

From (E11) and (E12) we can derive the optimal paths for our optimal control pair ${u_m}^*(t), {u_r}^*(t)$.

$${u_m}^* = \begin{cases} 0, & if\ \lambda \leq 0 \\ \min\left\{\frac{-\beta \pm \sqrt{\beta^2 + 4\alpha\lambda e^{\delta(t-t_0)}}}{2\alpha}, E(t) - \varepsilon\right\}, & if\ \lambda > 0 \end{cases} \tag{E15}$$

$${u_r}^* = \begin{cases} 0, & if\ \lambda \leq 0 \\ \frac{-\rho \pm \sqrt{\rho^2 + 4\kappa\lambda e^{\delta(t-t_0)}}}{2\kappa}, & if\ \lambda > 0 \end{cases} \tag{E16}$$

where $\varepsilon > 0$ is a small parameter ensuring the strict inequality on $u_m(t)$ is satisfied. Since u_m and $u_r \geq 0$ we can take the positive root.

The optimal control problem is solved using a forward-backward-sweep method (FBSM) to solve the two-point boundary problem for $c(t)$ and $\lambda(t)$ (Lenhart and Workman, 2007). The coupled system of equations to be solved consists of

$$\frac{dc}{dt} = E(t) - u_m(t)^* - u_r(t)^*, \tag{E17}$$

$$\frac{d\lambda}{dt} = -2b\gamma e^{-\delta(t-t_0)}(T(t)), \tag{E18}$$

where (E17) is solved forward in time and (E18) is solved backward in time, using a weighted update. We use a secant root-finding method to find the value of $\lambda(t_f)$ that satisfies (E6). We use RStudio V4.4.3 for all calculations (Posit team, 2023).

2.3 Parameter importance and sensitivity analysis

As the input parameters are uncertain, to assess how sensitive MACROM results are, we conducted a variance-based sensitivity analysis for each SSP. We varied seven key parameters within ranges reflecting current scientific uncertainty as outlined in Table 1. An explanation of how the parameter ranges were derived is available in Section S1. All analyses were conducted separately for each SSP.

Table 1. Key Parameters

Parameter	Name	Units	Default Value	Lower Range	Upper Range	Type
γ	TCRE	°C per 1,000 $GtCO_2$	0.45	0.27	0.63	Climate
Fm_1	Cost of 1st Gt mitigation	$USD per tonne CO_2	10	5	20	Abatement cost
Fm_{50}	Cost of 50th Gt mitigation	$USD per tonne CO_2	1000	800	1500	Abatement cost
Fr_1	Cost of 1st Gt removal	$USD per tonne CO_2	10	5	50	Abatement cost
Fr_{50}	Cost of 50th Gt removal	$USD per tonne CO_2	2000	1000	2500	Abatement cost
b	Economic damage coefficient	per °C	0.05	0.01	0.2	Economic
δ	Discounting	%	0.03	0.01	0.05	Economic

Using Latin Hypercube Sampling (LHS), we selected 20,000 parameter combinations with a uniform distribution using the R-package *"lhs"* (Carnell, 2006). For each parameter combination, we solved the full optimal control problem and analysed the sensitivity for the model outputs of total economic cost (E4), total mitigation deployed (E15), and total CDR deployed (E16). As TCRE affects the magnitude of temperature change in response to changing cumulative CO_2 emissions, for each parameter combination we calculated $c(t_f)$ using the sampled γ, substituted into (E2) to solve for (E6). This resulted in a unique $c(t_f)$ target for each parameter combination, but a constant temperature target of 1.5°C in 2100 across all model runs.

We calculated the Coefficient of Variation (CV) to measure the variability of 1) total damages and 2) total deployment of mitigation and CDR ($GtCO_2$) across the 20,000 parameter combinations. CV is calculated as the ratio of standard deviation to the mean, and provides a dimensionless measure of relative variability, enabling comparison across outputs (Shechtman, 2013). Once the CV was used to identify the variability of damages and deployment costs, a Sobol sensitivity analysis was used to identify which parameters were the key drivers of that variance (Sobol, 2001; Saltelli, 2008). We calculated both first-order and total-order Sobol indices. First-order indices capture the individual effects of each parameter on the solution, while total-order indices also include higher-order parameter interactions (Sobol, 2001). We used the "*SALib*" package (Herman and Usher, 2017) in Python for all Sobol analysis.

2.4 Delayed deployment analysis

To explore the impact of additional delays on the deployment of mitigation and CDR and the total costs, a delay factor was introduced to delay the implementation of the control variables for up to 70 years beyond 2020. The baseline emissions released for each SSP does not change; however, the different delays can change the optimal mix of mitigation and CDR used and the optimal timing of deployment compared to optimal solutions with no delays.

Across all 5 SSP baseline scenarios the default parameter set (Table 1) was used, allowing us to investigate how a delay in the availability of at-scale deployment affects the cost of deployment and temperature-related damage in each simulation. Independent delay periods were applied to mitigation and CDR control variables allowing each to be delayed from 0 to 70 years in 1-year increments (71 increments). A 70-year delay corresponds to deployment starting in 2090, allowing a decade of climate abatement to take place under the longest delay. In total 5,041 (71 yearly increments for mitigation x 71 year increments for CDR) unique delay combinations were run for each SSP. Delayed deployment implementation imposes a time-dependent constraint on the control variables but preserves the two-point boundary value problem structure of (E4), (E5) and (E6).

3. Results.

3.1 Optimal mitigation and removal pathways

Cost-optimal pathways favoured immediate use of mitigation and CDR in the absence of constraints on deployment timing, capacity or growth rate (Fig 1). Notably, the pathways represented interior solutions (where mitigation and CDR are deployed at intermediate levels), rather than immediately maximising either option. Optimal pathways to reach 1.5°C by 2100 all avoided a temperature overshoot. The pathways achieved net-negative cumulative emissions for the first few decades (Fig 1A) reducing global temperatures to a minimum between 2043 (SSP1) and 2063 (SSP5) (Table S2). Subsequently, reductions in abatement use occur from approximately 2040 onwards (Fig 1A), ensuring global mean surface temperature reached the constrained 1.5°C temperature target from below by 2100 (Fig 1B).

The scenarios achieved similar temperature trajectories, although abatement volume varied (Fig 1B, C, D). Mitigation and CDR deployment are used most in the first half of the century before decreasing to near zero. All solutions preferred mitigation over CDR, with mitigation making up between 55.5% to 57.9% of the total abatement deployed (Table S2). Total mitigation volume ranged from 492 $GtCO_2$ (SSP1) to 1,894 $GtCO_2$ (SSP5), and CDR volume ranged from 394 $GtCO_2$ (SSP1) to 1,374 $GtCO_2$ (SSP5) (Table S2). Due to its high projected emissions, SSP5 used substantially more mitigation and CDR than all the other SSP scenarios (3,268 $GtCO_2$ combined across mitigation and CDR in SSP5) contributing to higher abatement costs as a percentage of the projected GWP (Fig 1E, Table S2).

In the cost-optimal solutions, temperature-related damages, rather than mitigation and CDR deployment costs, represented the largest component of total costs for all SSPs (Fig 1E, F, Table S2). SSP1 had the highest proportion of costs resulting from temperature-dependent damages (90%), with only 10% of the overall expenditure resulting from abatement costs. Even in SSP5, which had the highest proportion of expenditure resulting from abatement solutions (33.9%), the majority of expenditure was still derived from temperature-dependent damage. For all other SSPs, temperature-dependent damages were between 66.1% and 84.6% of the overall expenditure (Table S2). As a percentage of projected yearly GWP, deployment costs declined following changes in the volume of mitigation and CDR deployed. At the same time, temperature-related damages declined over time as mitigation and CDR deployment affected cumulative CO_2 emissions. Over the full period of the simulation total deployment costs and temperature-related damages as a percentage of projected present-value GWP were highest in SSP3 (4.2%) and lowest in SSP1 (1.5%) (Table S2).

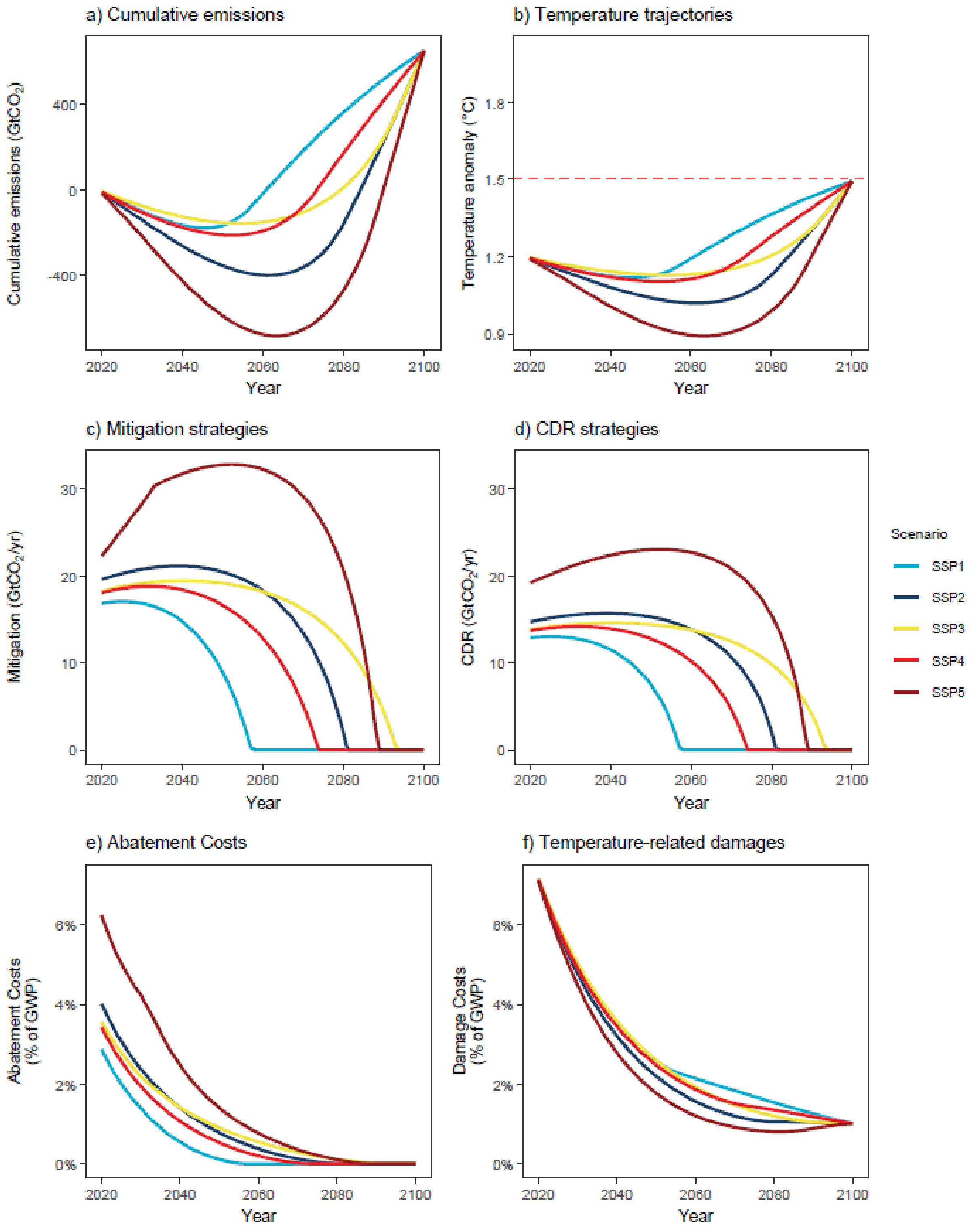


Fig 1 Comparison of optimal control results across 5 baseline SSP pathways. The six panels present optimal control model outputs for achieving the 1.5°C target under different SSP baseline scenarios (SSP1-SSP5), with default model parameters across all scenarios (Table 1). The panels show: (a) cumulative emissions trajectories; (b) temperature anomalies; (c) mitigation volume ($GtCO_2$); (d) CDR volume ($GtCO_2$); (e) annual cost of abatement as a proportion of GWP; and (f) annual temperature-dependent damage costs as a proportion of GWP. The red dashed line in panel (b) indicates the 1.5°C Paris Agreement target.

3.2 Sensitivity analysis

Total cost (the sum of deployment cost and temperature-related damage) over the 80-year period had the highest sensitivity to parameter uncertainty (compared with total deployment of mitigation or CDR), with CV ranging from 0.58 (SSP3) to 0.71 (SSP1) (Table S3). Across all SSPs, the discount rate (δ) and economic damage coefficient (b) were the largest drivers of variability in total costs, with Sobol total-order indices (S_T) varying from 0.50-0.62 for the economic damage coefficient and 0.43-0.55 for the discount rate (Fig 2, Table S4). The difference between first-order and total-order indices was <0.1, indicating modest interaction effects between parameters for all SSPs (Table S4). The cost of the 1st or 50th $GtCO_2$ for either mitigation or CDR, which set the marginal cost curve, had an almost negligible effect (<0.05) on total cost (Fig 2, Table S4).

Compared to total cost, the total amount of mitigation deployed showed less sensitivity to parameter uncertainty, with CV ranging from 0.15 (SSP3) to 0.24 (SSP1) (Table S3). The cost of the 1st $GtCO_2$ removed (Fr_1) and TCRE (γ) were the primary sources of uncertainty in all SSPs, excluding SSP5 (Fig 2, Table S4). The cost of the 1st $GtCO_2$ removed was the dominant parameter in SSP2 (S_T = 0.52), SSP3 (S_T = 0.57), SSP4 (S_T = 0.45) and SSP5 (S_T = 0.69), while TCRE was the dominant parameter in SSP1 (S_T = 0.64) (Table S4). TCRE was the secondary driver of outcome variability for SSP2 (S_T = 0.26), SSP3 (S_T = 0.25) and SSP4 (S_T = 0.39) (Table S4). For SSP1, the secondary driver of variability was the cost of the 1st $GtCO_2$ removed (S_T = 0.25) (Table S4). The cost of the 50th $GtCO_2$ removal was the secondary driver for SSP5 variability (S_T = 0.31) but was primarily due to interaction effects with other parameters as shown by the large difference between first-order (S_1) and total-order indices (S_T -S_1 = 0.29) (Fig 2, Table S4).

Finally, total CDR deployment had CV's ranging from 0.23 (SSP3) to 0.34 (SSP1) (Table S3). The cost of the 1st $GtCO_2$ of removal (Fr_1) and TCRE (γ) were the primary drivers of variability across all scenarios (Fig 2, Table S4). TCRE was the dominant parameter for SSP1 (S_T = 0.59), while the cost of the 1st $GtCO_2$ of removal was the second largest driver variability (S_T = 0.31) (Table S4). In contrast, for the remaining SSPs the cost of the 1st $GtCO_2$ of removal was the primary driver (S_T = 0.47-0.78), with TCRE the second largest driver of variability (S_T = 0.12-0.36) (Table S4). SSP5 was the only scenario with influential interaction effects for the economic damage coefficient (S_T -S_1 = 0.11), cost of the 1St $GtCO_2$ removal (S_T -S_1 = 0.29) and the cost of the 50th $GtCO_2$ removal (S_T -S_1 = 0.30) (Table S4).

Declines in abatement deployment varied across SSPs. Mean mitigation and CDR usage in SSP1 declined rapidly to near-zero before 2060 (Fig S3), shortly after 2060 for SSP4 (Fig S6), between 2060 and 2080 for SSP2 (Fig S4) and after 2080 for SSP3 (Fig S5) and SSP5 (Fig S7). As a result, abatement costs peaked early across all SSPs (Fig S3-S7). Temperature-dependent climate damage costs started higher at the beginning of the simulation, decreased towards the middle of the century and then remained flat or rose slightly as mitigation and CDR usage decreased and temperatures increase again towards 1.5°C in the last several decades before 2100 (Fig S3-S7).

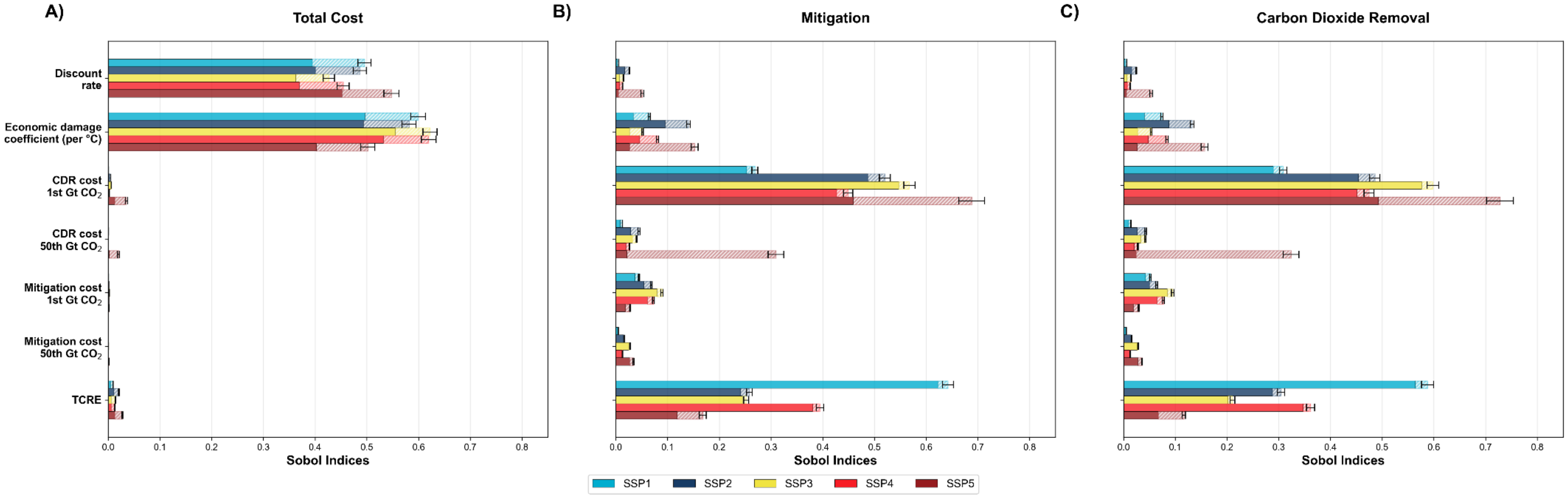


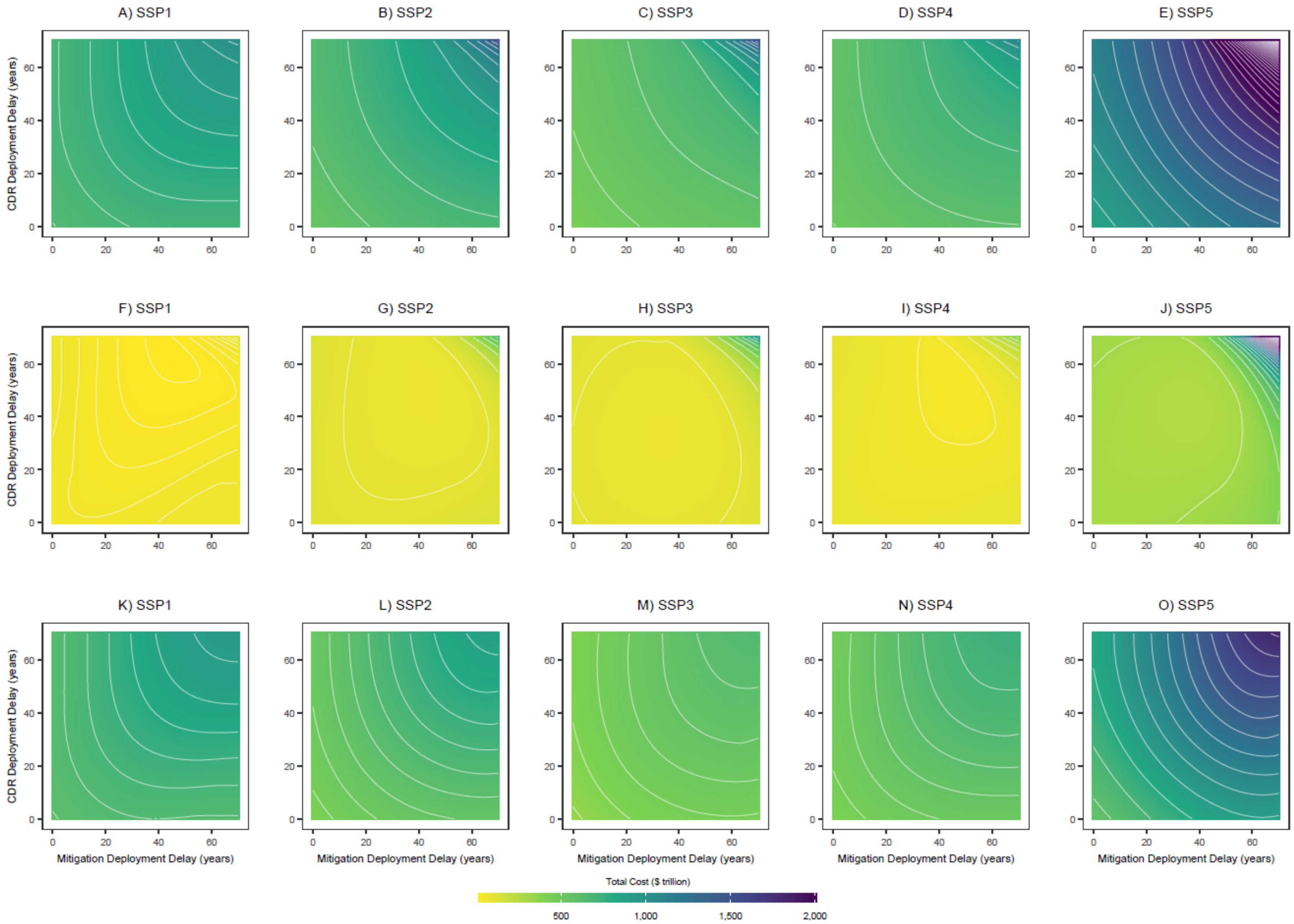
Fig 2. Parameter importance analysis using Sobol sensitivity indices for key model outcomes. The three panels show total-order Sobol indices quantifying the relative importance of model parameters in explaining variance in: A) total cost; B) total mitigation deployment; and C) total CDR deployment. Analysis conducted using 20,000 Latin hypercube samples across parameter ranges specified in Table 1, using SSP1-SSP5 baseline scenarios. Error bars represent confidence intervals for the Sobol index total-order results. Solid bars represent the first-order results, while diagonal lines indicate interaction effects.

3.3 Delayed deployment

We implemented delays in deployment to model potential technological delays in CDR rollout, allowing us to compare the changes to the optimal use of mitigation and CDR compared to no deployment constraints and the effect on total costs. All SSPs showed increasing total costs as deployment of either mitigation or CDR was delayed, with the maximum costs ranging from $643 trillion (SSP1) to $5,147 trillion (SSP5). Total costs were cheapest with immediate abatement (no delay). The curved contour lines, and reduced space between contour lines as delays increased, indicated that costs increased non-linearly, becoming increasingly more expensive as abatement delays increased (Fig 3A-E). Total costs increased more steeply with mitigation delays (horizontal axis) than CDR delays (vertical axis) (Fig 3A-E).

The contour patterns for abatement costs displayed bowl-shaped structures. Global cost minimum regions occurred after abatement delay (Fig 3F-J), although the cost-optimal delay period varies between SSPs. However, the quantity and closeness of the contour lines in the top right of each plot indicated an abrupt acceleration of abatement costs with very long delays (>60 years) (Fig 3F-J). This acceleration is most strongly identifiable in SSP5 (Fig 3J).

Temperature-related damage costs showed a monotonic increase with deployment delays across all scenarios (Fig 3K-O). For SSP1-SSP4 the space between contour lines increased as abatement delays increased, indicating the growth rate of temperature damages decreased as abatement delays increased (Fig 3K-N). This pattern was not evident for SSP5 (Fig 3O).


A) SSP1
B) SSP2
C) SSP3
D) SSP4
E) SSP5
F) SSP1
G) SSP2
H) SSP3
I) SSP4
J) SSP5
K) SSP1
L) SSP2
M) SSP3
N) SSP4
O) SSP5
CDR Deployment Delay (years)
Mitigation Deployment Delay (years)
0
20
40
60
Total Cost ($ trillion)
500
1,000
1,500
2,000

431

Fig 3 Impact of mitigation and CDR deployment delays on cost of abatement deployment and temperature-related damage, and combined deployment and damage costs across SSP scenarios. The panels present contour plots showing how delays in mitigation (x-axis) and CDR (y-axis) deployment affect costs for each SSP scenario. Delays range from 0-70 years in 1-year increments. Figures A-E sum of abatement costs and temperature related damages. Figures F-J abatement (mitigation and CDR) deployment costs. Figure K-O temperature related damages. Colour scales are capped at the 99.5th percentile ($2,000 trillion USD) to enhance visual discrimination across the primary data range; values exceeding this threshold are displayed at maximum saturation.

4. Discussion

MACROM is designed to investigate the influence of deployment costs and temperature-related damages on optimal abatement pathways to achieve a specified temperature target. Here, we use MACROM to explore optimal unlimited deployment of mitigation and carbon dioxide removal (CDR) to achieve the Paris Agreement target to limit warming to 1.5°C by 2100.

In the absence of constraints on abatement timing, growth rates or scale, the most cost-optimal approach to achieve the Paris Agreement target was to immediately deploy high levels of both mitigation and CDR across all socio-economic scenarios. Most unexpectedly, this optimal deployment approach meets the Paris Agreement target from below – with mean global temperature decreasing to as low as 0.9°C, before rising to 1.5°C by 2100. This is opposite to the real-world expectation that the Paris Agreement target will only be met from above via an overshoot (Reisinger *et al.*, 2025).

The primary reason for MACROM's no-overshoot approach is: 1) the disparity between temperature-related damage and abatement costs, and; 2) the lack of constraints on mitigation or CDR. As a result, the optimal solution minimises relatively expensive temperature-related damage in the initial decades by using high levels of comparatively cheap, unlimited mitigation and CDR to drive down global temperature. The temperature is then allowed to increase later in the century, where expensive damages are more heavily discounted, by reducing deployment of mitigation and CDR. The strategy of immediate, high use of abatement to avoid an overshoot is optimal, even for temperature targets below 1.5°C. For example, if the temperature target is set to 1.2°C (i.e. temperature in 2100 must not change from 2020), immediate, high levels of abatement is still used to drive the temperature below target, but with mitigation and CDR quantities remaining higher for longer in comparison with the 1.5°C target (Fig S8).

The volume of CDR deployed in our simulations is well outside what is currently considered feasible (Shukla *et al.*, 2022), yet near-term emissions mitigation is still necessary for minimizing total costs. In addition to keeping costs lower, emissions mitigation is also necessary to reduce the risks of global temperature rising above 1.5°C permanently if future CDR capacity cannot meet demand (Fuss *et al.*, 2018; Hilaire *et al.*, 2019; Lamb *et al.*, 2024; Reisinger *et al.*, 2025; UNEP, 2025), a possibility not explored here. Therefore, the immediate, large-scale use of emissions mitigation plays a key role in achieving the Paris Agreement irrespective of the present or future availability of CDR.

Temperature-related damages are the primary driver of total costs, due to their magnitude compared to abatement costs. The increase in temperature-related damages with abatement delays is intuitively understandable – the longer we wait to act, the more severe the impacts of increased global temperature on Gross World Product (GWP).

Conversely, the non-linear relationship between medium term (30-60 year) abatement delays and abatement costs is surprising. Abatement costs are affected by the discount rate and the scale of abatement deployed in a given year. Over time, the discount rate decreases the present-value cost of abatement, favouring acting in the future when costs are cheaper. However, the marginal cost of abatement makes it increasingly more costly to deploy at larger scales, favouring balanced usage over time. Additionally, longer delays inherently increase the scale of deployment required to reach 1.5°C due to the shorter timeline. Our results show that the interaction of these factors finds that it is cost-optimal to delay abatement. However, when combining optimised abatement costs with temperature-related damages, MACROM recommends early abatement action. This is consistent with many other studies that recommend early or immediate climate action over delay (Moore and Diaz, 2015; Rogelj *et al.*, 2019; Cerasoli and Porporato, 2023; Kikstra and Waidelich, 2023; Adun *et al.*, 2024; Ganti *et al.*, 2024; Schaber *et al.*, 2024)

The discount rate and economic damage coefficient were the primary drivers of variance in cost outcomes. This finding was consistent across all SSPs. Surprisingly, the marginal cost of mitigation and CDR exerted minimal influence on total costs, despite the wide range of costs sampled. The parameterisation of economic damage and discounting remains contentious in the literature, with limited consensus regarding methodological approaches. Discount rate has been demonstrated to have a significant impact on recommended climate action (Stern, 2008; Dietz and Stern, 2015; Moore and Diaz, 2015; DeFries *et al.*, 2019; Hilaire *et al.*, 2019; Cerasoli and Porporato, 2023). Additionally, ongoing debate exists regarding whether a constant discount rate is the most appropriate economic approach to assessing the costs of climate-related damage and abatement (Arrow *et al.*, 2013, 2014; Cherbonnier and Gollier, 2023). Discount rates and economic damage calculations inherently involve value judgements concerning the relative importance of intergenerational equity (Asayama and Hulme, 2019; Ganti *et al.*, 2024). Our results add to the growing consensus that discount rate and economic damage of climate change calculations fundamentally influence optimal climate abatement pathways, warranting further study.

MACROM bridges cost-benefit and cost-minimisation IAM approaches by treating the 1.5°C Paris Agreement target as a binding constraint while minimising both abatement costs and temperature-related damages. The intentional relaxation of feasible abatement capacity reveals the theoretical requirements for achieving stringent temperature targets at minimum cost but limits the model's ability to provide prescriptive pathways. MACROM contains no climate-system feedbacks, so changes to the effectiveness of carbon sinks or self-perpetuating climate feedbacks (such as the release of greenhouse gases from melting permafrost) (Allen *et al.*, 2022) are not included in the model. There are also no economic feedbacks, so the impact of diverting significant levels of global economic activity towards climate abatement, at the expense of other economic investment, is not modelled. Nevertheless, MACROM's simplicity and use of optimal control theory is also a source of flexibility. We have focused on the Paris Agreement temperature target in this study, but the temperature target, time horizon, parameter values and control constraints can be adjusted without affecting the underlying mathematical framework.

The optimal control framework used by MACROM provides the ability to extend the time horizon in future research to examine the effects on total cost of achieving the temperature target at different specified date, or with a free terminal time, where the objective function is minimised over all possible controls and time frames (Lenhart and Workman, 2007). This would allow us to ascertain whether, for example, a cost-optimal solution exists that would achieve the 1.5°C target with only a minor delay to the target date. Optimal control problems also have the flexibility to add constraints to the control variables, which would allow us to evaluate the impact of adding realistic growth rates and capacity limits to mitigation and CDR. From this, we could examine the impact on total costs, and the feasibility of achieving the Paris Agreement 1.5°C by 2100, including outcomes such as peak temperature and years above 1.5°C, which would allow us to examine under what conditions a temporary overshoot would still be recoverable this century.

5. Conclusion

Here we present MACROM, a simple climate-economic model to project cost-optimal deployment of mitigation and CDR to achieve a desired temperature target. MACROM contributes a new approach to evaluating future climate actions, using optimal control theory to determine the most cost-effective use of mitigation and CDR to achieve the Paris Agreement target. The aim of MACROM was to reveal insights about the trade-offs of deployment costs and temperature-related damages on optimal pathways to achieve the Paris Agreement target, without limiting solutions to current assumptions about feasible future technology. The analysis of the optimal strategies demonstrates that, even without restrictions on the use of CDR, cost-optimal solutions require the immediate use of emissions mitigation, alongside CDR. Temperature-related economic damages are more costly than implementing abatement solutions, and optimal solutions are strongly influenced by the choices made when deciding economic parameter values. Despite its exploratory nature, MACROM offers insight into the scale of climate action required to achieve the Paris Agreement. By using optimal control theory as the framework, MACROM can be customised for future research on optimal pathways under different constraints or targets.

Data availability

Emissions and economic data forecasts to conduct all analyses were sourced from (Riahi *et al.*, 2017). A copy of the data is included in the code repository.

Code availability

The analysis was performed with Rstudio and Python. The scripts to conduct the analysis and replicate all figures are available at Zenodo (https://doi.org/10.5281/zenodo.18463951).

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Supplementary Information.

S1. Model parameters

Transient Climate Response to cumulative CO_2 Emissions (TCRE)

The Transient Climate Response to cumulative CO_2 Emissions (TCRE, γ) affects the sensitivity of the climate system to atmospheric CO_2. This in turn affects the cumulative CO_2 emissions target at the final time. The IPCC Sixth Assessment Report (2021) states the TCRE is likely in the range of 1.0°C to 2.3°C per 1000 GtC (gigatonnes of carbon), with a best estimate of 1.65°C per 1000 GtC (Masson-Delmotte *et al.*, 2021). For modelling purposes, these values need to be converted from CO to CO_2 units by dividing by 3.67 (the ratio of molecular weights of CO_2 to C). This conversion yields a TCRE range of approximately 0.27°C to 0.63°C per 1000 $GtCO_2$, with a central estimate of 0.45°C per 1000 $GtCO_2$.

Cost of 1st and 50th $GtCO_2$ mitigation

The marginal cost curve for mitigation is derived from two parameter values: the cost of the 1st $GtCO_2$ (Fm_1) and the cost of the 50th $GtCO_2$ (Fm_{50}) mitigated (see Section S2 for full derivation). We have taken an approach that assumes that a range of intervention methods will be required, starting with low-cost efficiency improvements, to novel technology, potentially undeveloped, and therefore with unknown cost at present (Edelenbosch *et al.*, 2024; Lamb *et al.*, 2024). The cost per unit of mitigation is informed by valuations from Integrated Assessment Models (IAMs). Carbon mitigation costs are estimated at $300-500 per tonne in DICE (Nordhaus, 2014), $50-200 per tonne in MESSAGE/REMIND (Baumstark *et al.*, 2021) and $220-500 per tonne in IMAGE (Stehfest *et al.*, 2014). The right hand tail of the marginal cost curve is based on recent research using more comprehensive damage functions that suggests a range of $200-1000 per tonne (van der Wijst *et al.*, 2023).

The default marginal cost curve is formulated using $10 USD/$tCO_2$ for the 1st $GtCO_2$ and $1,000 for the 50th $GtCO_2$. For the parameter sensitivity analysis, we have used a range from $5-20 USD/$tCO_2$ for the 1st $GtCO_2$ (Fm_1) and $800-1,500 for the 50th $GtCO_2$ (Fm_{50}).

Cost of 1st and 50th $GtCO_2$ CDR

The marginal cost curve for CDR is derived from two parameter values: the cost of the 1st $GtCO_2$ (Fr_1) and the cost of the 50th $GtCO_2$ (Fr_{50}) mitigated (see Section S2 for full derivation). As with mitigation, we have assumed a range of interventions will be required. MACROM allows for the deployment of unlimited CDR, therefore it is likely that more expensive solutions, including as-yet undeveloped or unproven technologies, will be required, especially in scenarios where high volumes of CDR are needed. The most widely forecast CDR methods include afforestation/reforestation (\$0-240 USD/tCO_2), bioenergy with carbon capture and storage (\$15-400 USD/tCO_2), and direct air carbon capture and storage (\$25-1,000 USD/tCO_2), but estimates of CDR methods like enhanced rock weathering are upwards of \$3,000 USD/tCO_2 (Fuss *et al.*, 2018). Additionally, cheaper land based CDR methods, such as afforestation/reforestation, may have practical deployment constraints, due to their requirements for land and water availability and competition with demand for agricultural land, limiting their capacity (Fuss *et al.*, 2018; Strefler *et al.*, 2018; Hilaire *et al.*, 2019; Ganti *et al.*, 2024; Marshall, Grubert and Warix, 2025).

The default marginal cost curve is formulated using \$10 USD/tCO_2 for the 1st GtCO_2 and \$2,000 USD/tCO_2 for the 50th GtCO_2. For the parameter sensitivity analysis, we have used a range from \$5-50 USD/tCO_2 the 1st GtCO_2 (Fr_1), and \$1,000-2,500 USD/tCO_2 for the 50th GtCO_2 (Fr_{50}).

Economic damage coefficient

Evaluating the cost of increasing temperatures is a challenging exercise. Models generally focus on the effects on gross world product (GWP), but this approach has known shortcomings. Economic assessment that focus on GWP impact fail to capture the full cost of global warming because they exclude the costs of lost ecosystem services, tipping points, compound extreme events and catastrophic damages (Edenhofer *et al.*, 2015; DeFries *et al.*, 2019; Hilaire *et al.*, 2019; Cerasoli and Porporato, 2023; Kikstra and Waidelich, 2023). Attempts to value ecosystem services, for example, estimate a value almost double that of GWP (Costanza, 2012; Costanza *et al.*, 2014), but limited data and uncertainty of how to create a valuation for public goods and services makes estimates of costs, and therefore damages, difficult (Farber, Costanza and Wilson, 2002; de Groot *et al.*, 2012).

While IAMs can find damage as low as 0.29% of GWP (Warren *et al.*, 2021), bottom-up approaches estimate 10-12% (van der Wijst *et al.*, 2023), showcasing the wide range of estimates in the literature. We use a value of 5% of GWP as our default value, falling in between values from different methodologies. To account for known shortcomings in relying on GWP forecasts only, we use values between 1% and 20% in our sensitivity analysis. The high end of this range makes some allowance for unknown ecosystem service costs that may occur.

Discount rate

Discount rates have significant influence on shaping climate policy recommendations, with widespread discussions of suitable rates in the scientific literature (Stern, 2008; Arrow *et al.*, 2013; Greaves, 2017; Heal, 2017; DeFries *et al.*, 2019; Hilaire *et al.*, 2019; Groom *et al.*, 2022; Cherbonnier and Gollier, 2023). The use of discount rates can be interpreted as a moral (rather than economic) choice and raises concerns about intergenerational equity and the burdens placed on future generations (Weitzman, 1998; Dasgupta, Mäler and Barrett, 1999; Stern, 2008; Roche, 2016; Asayama and Hulme, 2019).

For our sensitivity analysis we use discount rates between 1% to 5%, covering the range of values most discussed in economic policy, with a default rate of 3%.

Emissions and Gross World Product Projections

Projections for CO_2 emissions and gross world product are sourced from (Riahi *et al.*, 2017).

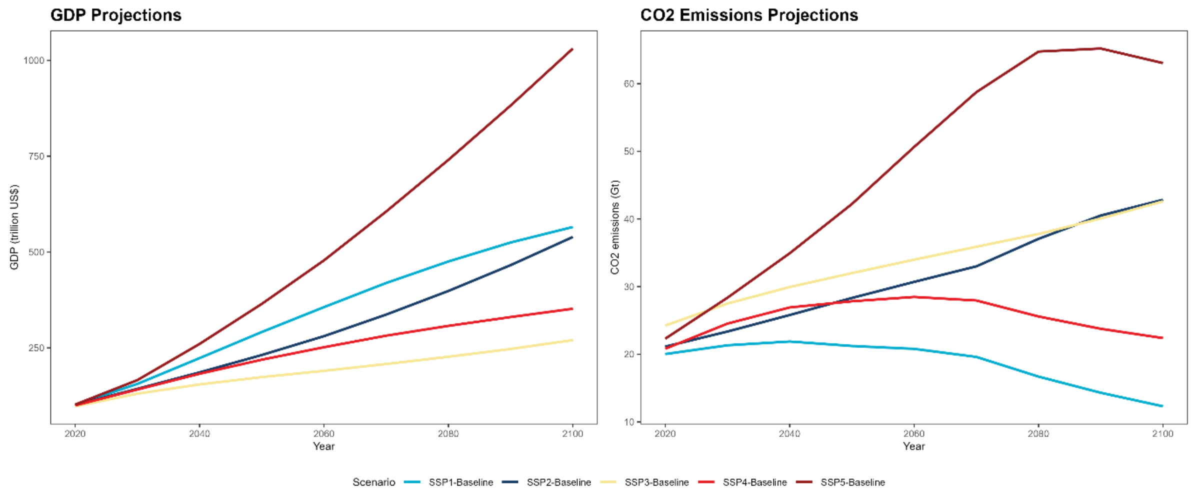

Fig S1. Baseline gross world product and CO_2 emissions forecasts.

S2. Marginal cost function

The marginal cost for both mitigation and carbon dioxide removal (CDR) follows a quadratic functional form.

$$MC(x) = \alpha x^2 + \beta x,$$

where x represents the cumulative quantity of CO_2 (in $GtCO_2$) either mitigated or removed, and $MC(x)$ is the marginal cost (in trillion USD per $GtCO_2$) of abating the x-th unit. The function is constrained to pass through the origin, such that $MC(0) = 0$.

Parameter estimation for mitigation

For mitigation, the parameters α and β are determined using two calibration points:

$MC(1) = 0.01$ (the marginal cost of the first Gt CO_2 mitigated)

$MC(50) = 1.0$ (the marginal cost of the fiftieth Gt CO_2 mitigated)

This yields the system of equations:

$$\alpha(1)^2 + \beta(1) = 0.01$$

$$\alpha(50)^2 + \beta(50) = 1.0$$

Solving this system using Gaussian elimination:

$$\beta = \left(\frac{1.0 - 0.01(50)^2}{(1)^2}\right) \Big/ \frac{50 - (50)^2}{1},$$

$$\alpha = \frac{1}{(1)^2}(0.01 - \beta \cdot 1).$$

Evaluating these expressions gives $\alpha = 2.04 \times 10^{-4}$ and $\beta = 9.8 \times 10^{-3}$.

Parameter estimation for CDR

For CDR, we use analogous calibration points with different values to reflect the anticipated higher costs of carbon removal:

$MC(1) = 0.01$ (the marginal cost of the first Gt CO_2 removed)

$MC(50) = 2.0$ (the marginal cost of the fiftieth Gt CO_2 removed)

Following the same solution procedure and using the notation κ and ρ for the CDR parameters, we obtain $\kappa = 6.1 \times 10^{-4}$ and $\rho = 9.4 \times 10^{-3}$.

Total cost functions

The total cost of abatement is obtained by integrating the marginal cost function. For mitigation, the total cost F_m of mitigating u_m $GtCO_2$ is:

$$F_m(u_m) = \int_0^{u_m} \alpha x^2 + \beta x \,\mathrm{d}x,$$

$$F_m(u_m) = \frac{\alpha}{3}{u_m}^3 + \frac{\beta}{2}{u_m}^2.$$

Similarly, for CDR, the total cost F_r of removing u_r Gt CO_2 is:

$$F_r(u_r) = \int_0^{u_r} \kappa x^2 + \rho x \,\mathrm{d}x,$$

$$F_r(u_r) = \frac{\kappa}{3}{u_r}^3 + \frac{\rho}{2}{u_r}^2,$$

where F_m and F_r are expressed in trillion USD.

The marginal cost curves are shown below.

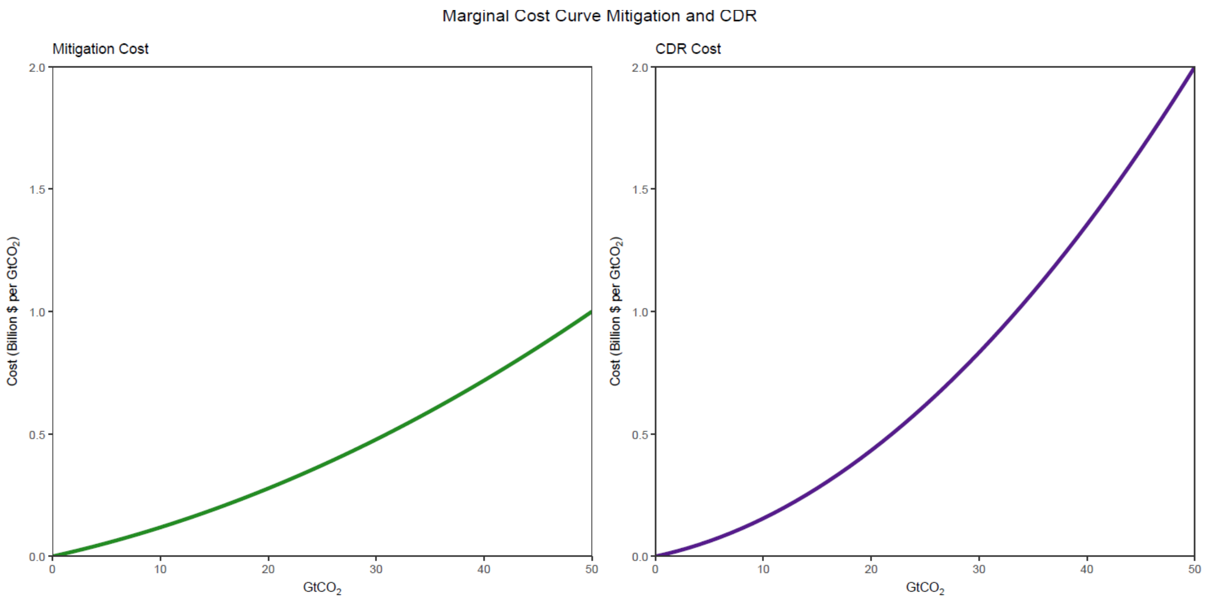

Fig S2. Mitigation and CDR marginal cost curve derived from default values (Table 1).

S3. Results

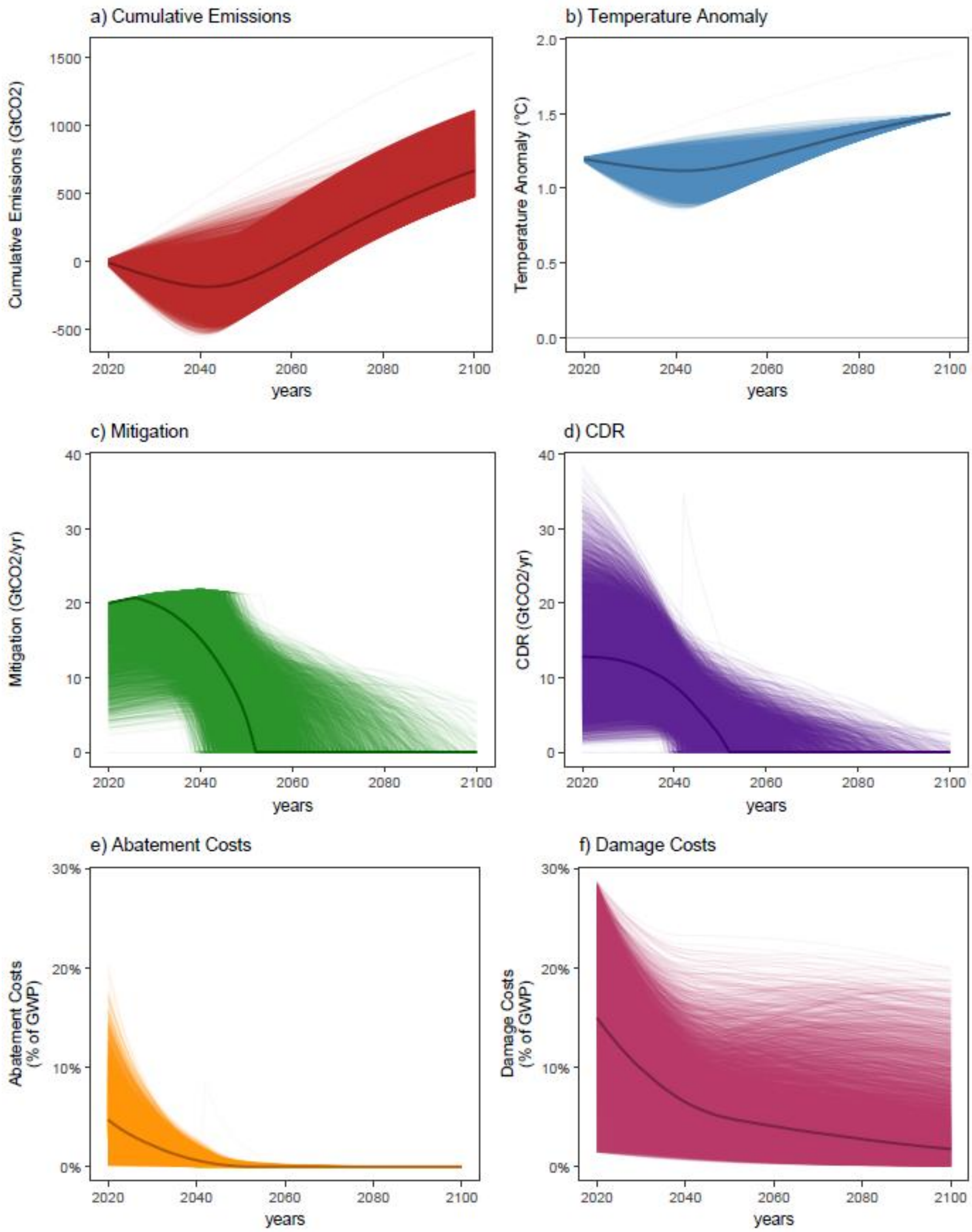

Fig S3 Outcomes for SSP1-Baseline scenario using Latin hypercube sampling. The six panels display results from 20,000 uniformly sampled parameter combinations applied to the optimal control model under the SSP1-Baseline scenario. Individual trajectories are shown as transparent lines with the ensemble mean highlighted in bold.

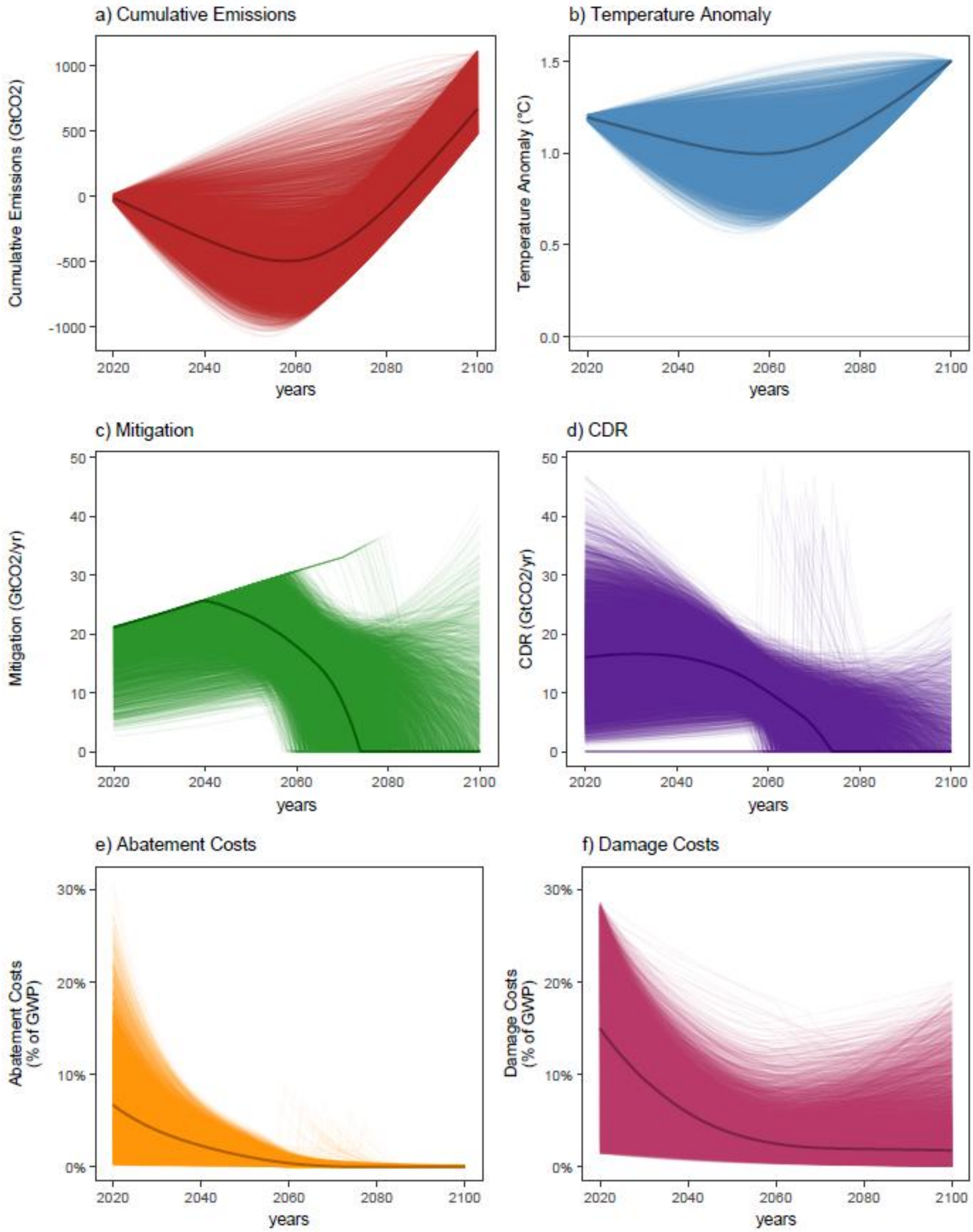

Fig S4 Outcomes for SSP2-Baseline scenario using Latin hypercube sampling. The six panels display results from 20,000 uniformly sampled parameter combinations applied to the optimal control model under the SSP2-Baseline scenario. Individual trajectories are shown as transparent lines with the ensemble mean highlighted in bold.

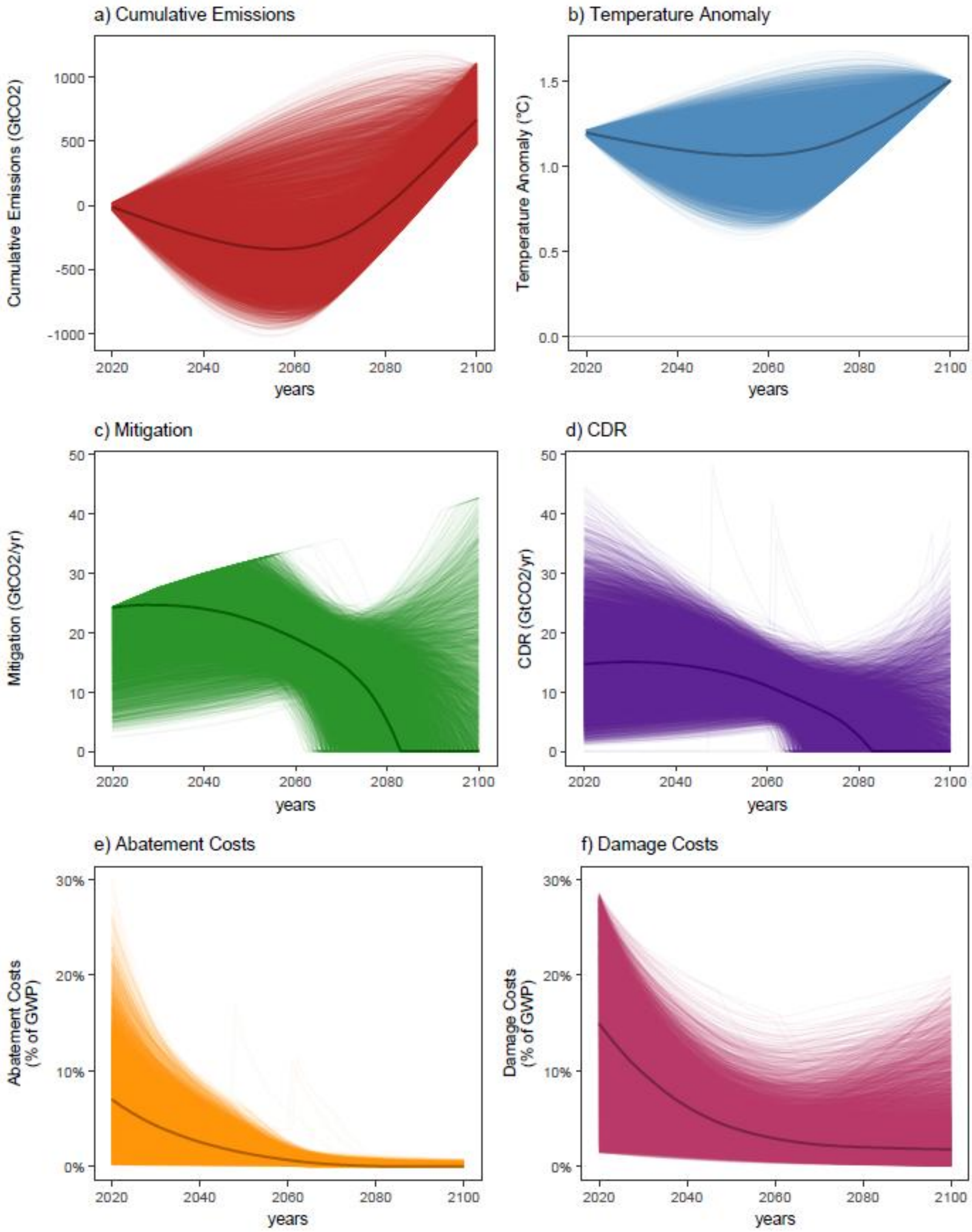

Fig S5 Outcomes for SSP3-Baseline scenario using Latin hypercube sampling. The six panels display results from 20,000 uniformly sampled parameter combinations applied to the optimal control model under the SSP3-Baseline scenario. Individual trajectories are shown as transparent lines with the ensemble mean highlighted in bold.

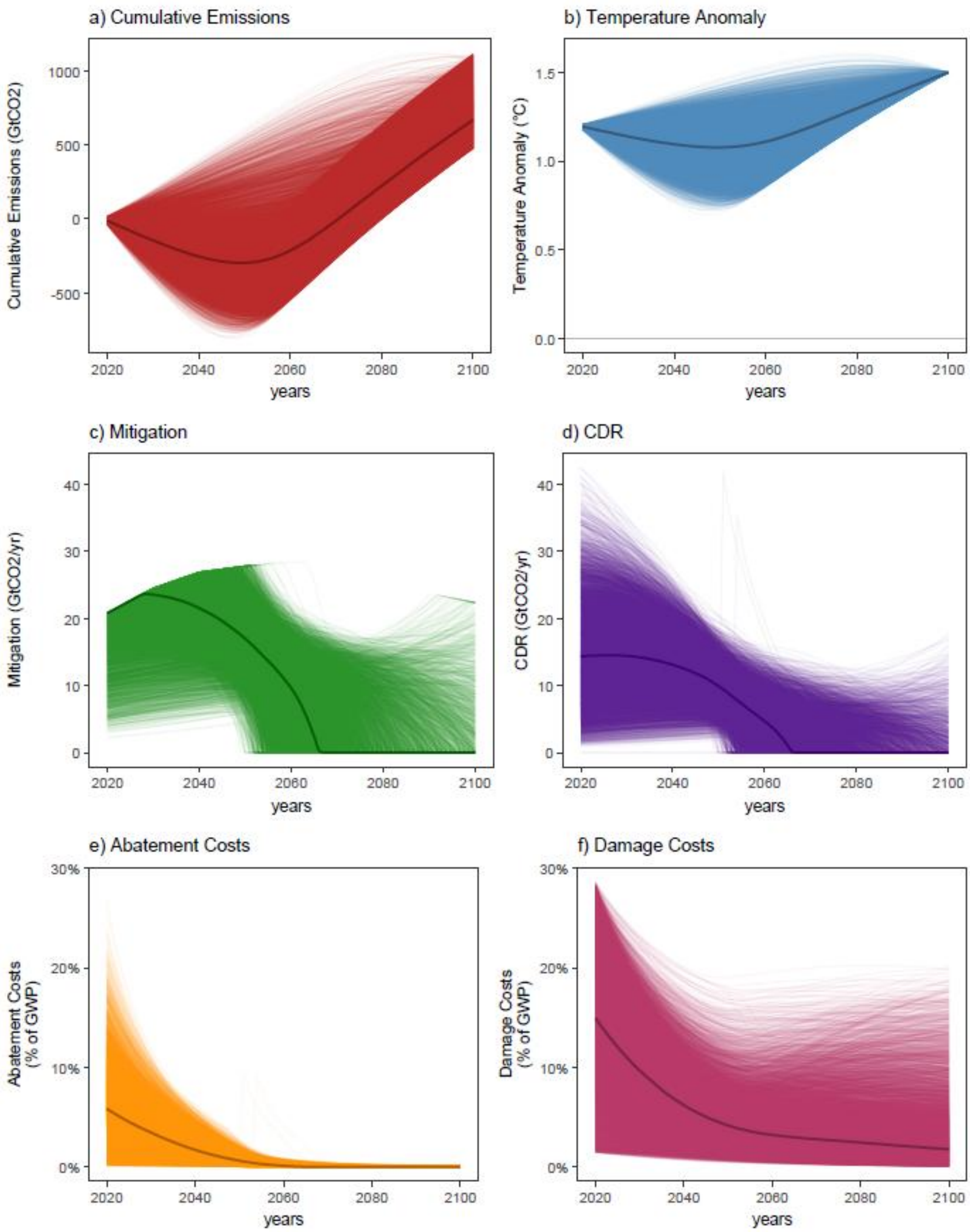

Fig S6 Outcomes for SSP4-Baseline scenario using Latin hypercube sampling. The six panels display results from 20,000 uniformly sampled parameter combinations applied to the optimal control model under the SSP4-Baseline scenario. Individual trajectories are shown as transparent lines with the ensemble mean highlighted in bold.

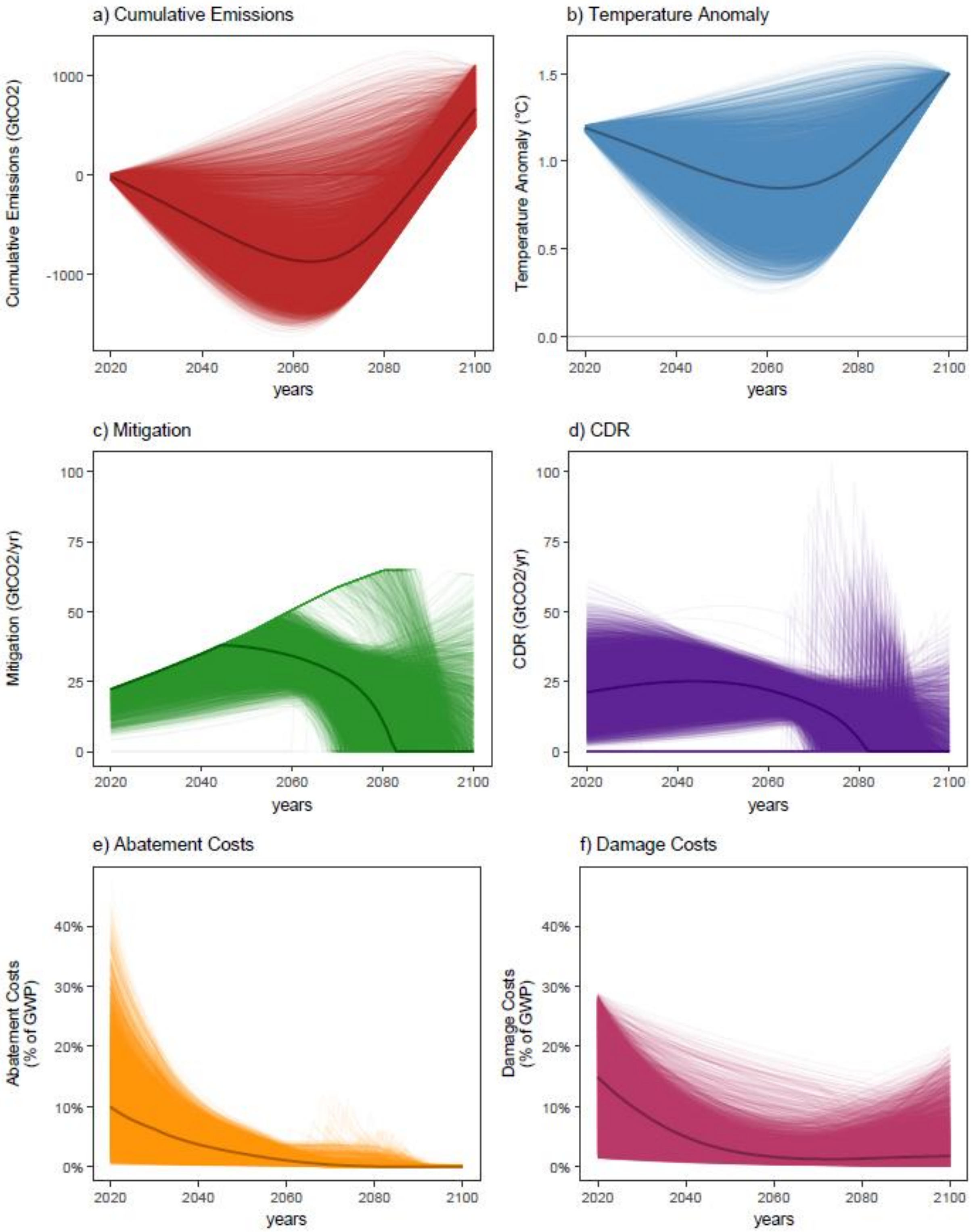

Fig S7 Outcomes for SSP5-Baseline scenario using Latin hypercube sampling. The six panels display results from 20,000 uniformly sampled parameter combinations applied to the optimal control model under the SSP5-Baseline scenario. Individual trajectories are shown as transparent lines with the ensemble mean highlighted in bold.

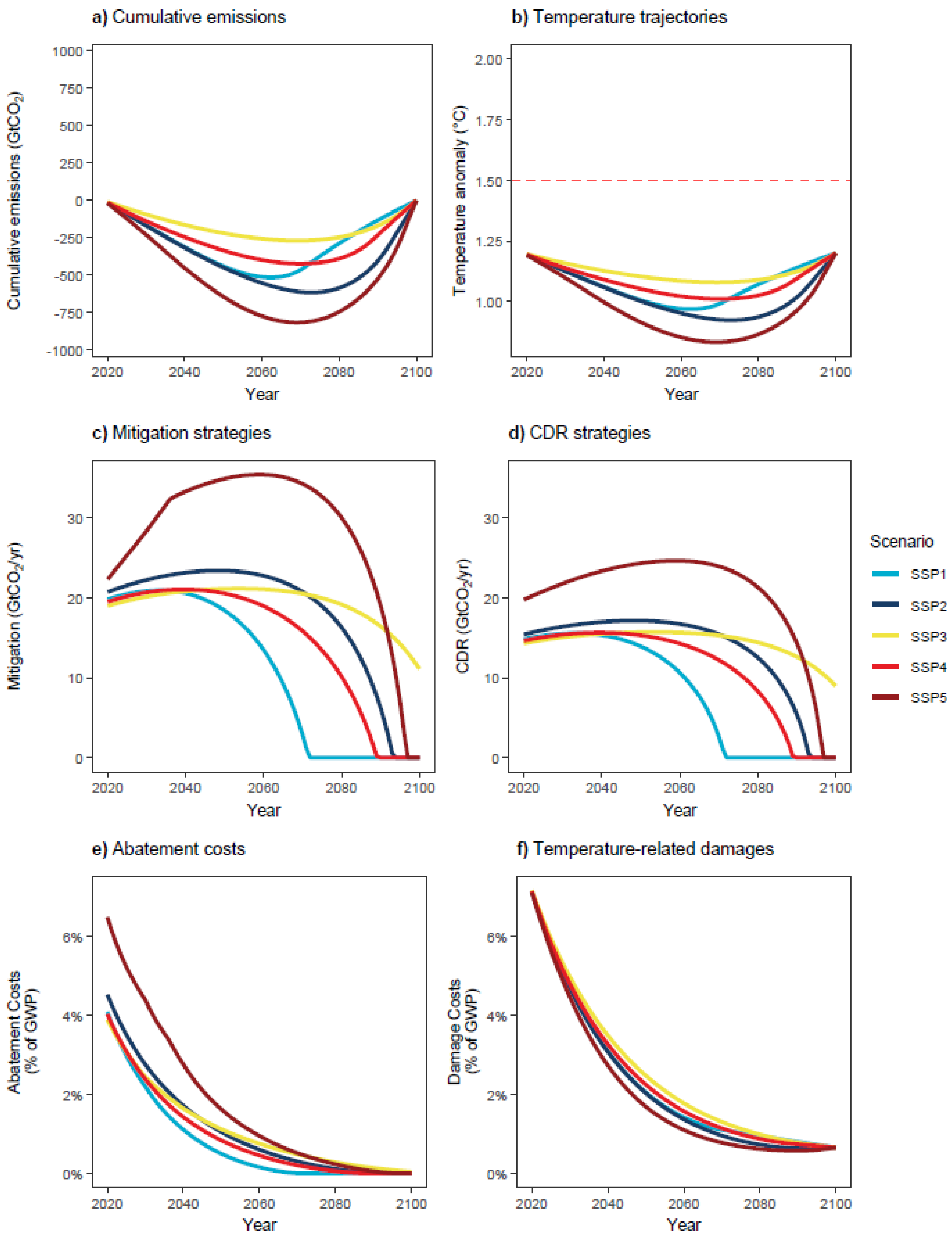

Fig S8 Comparison of optimal control results across 5 baseline SSP pathways with a temperature target of 1.2°C. The six panels present optimal control model outputs for achieving the 1.2°C target under different SSP baseline scenarios (SSP1-SSP5), with default model parameters across all scenarios (Table 1). The panels show: (a) cumulative emissions trajectories; (b) temperature anomalies; (c) mitigation volume ($GtCO_2$); (d) CDR volume ($GtCO_2$); (e) annual cost of abatement as a proportion of GWP; and (f) annual temperature-dependent damage costs as a proportion of GWP. The red dashed line in panel (b) indicates the 1.5°C Paris Agreement target.

Table S2. Optimal climate intervention strategies under five SSP baseline scenarios

Scenario	Year of lowest global temp.	Total mitigation (GtCO2)	Total CDR (GtCO2)	Mitigation % of abatement	Mitigation cost (trillion $ USD)	Removal cost (trillion $ USD)	Temp. damages cost (trillion $ USD)	Total cost (trillion $ USD)	Abatement as % of total cost	Temp. damage as % of total cost	Mitigation as % GWP	Removal as % of GWP	Temp. damages as % GWP	Total climate change costs as % GWP
SSP1	2043	491.9	394.3	55.5%	23.7	17.4	369.9	411.0	10.0%	90.0%	0.1%	0.1%	1.3%	1.5%
SSP2	2060	1073	816.5	56.8%	63.8	44.4	379.0	487.3	22.2%	77.8%	0.3%	0.2%	1.6%	2.0%
SSP3	2061	1198.1	890.8	57.4%	89.5	60.9	487.9	638.4	23.6%	76.4%	0.6%	0.4%	3.2%	4.2%
SSP4	2053	813.3	624.3	56.6%	50.4	35.5	470.9	556.8	15.4%	84.6%	0.3%	0.2%	2.4%	2.8%
SSP5	2063	1893.6	1374.5	57.9%	169.4	118.7	560.7	848.7	33.9%	66.1%	0.4%	0.3%	1.4%	2.1%

Optimal deployment strategies and associated costs for achieving the 1.5°C temperature target by 2100 across five SSP baseline scenarios. Results show the cost-minimising combination of emissions mitigation and carbon dioxide removal under default parameter assumptions (Table 1). All costs and climate impacts are reported in both absolute terms ($GtCO_2$ or trillion$ USD) and as percentages of global world product (GWP).

Table S3. Coefficient of variation for optimal strategies under parameter uncertainty across SSP scenarios

Scenario	Total Cost	Total Mitigation	Total Removal
SSP1	0.71	0.24	0.34
SSP2	0.64	0.16	0.24
SSP3	0.58	0.15	0.23
SSP4	0.64	0.18	0.26
SSP5	0.66	0.17	0.24

Relative variability (coefficient of variation) in optimal outcomes across 20,000 parameter combinations for each SSP baseline scenario, quantifying sensitivity to parameter uncertainty defined in Table 1.

Table S4. Sobol sensitivity indices for cost parameters across Shared Socioeconomic Pathways (SSPs).

Sobol indices of Total Cost ($)										
Cost Category	**SSP1**		**SSP2**		**SSP3**		**SSP4**		**SSP5**	
	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T
Discount rate	0.39 ± 0.01	0.50 ± 0.01	0.40 ± 0.01	0.49 ± 0.01	0.36 ± 0.01	0.43 ± 0.01	0.37 ± 0.01	0.45 ± 0.01	0.45 ± 0.01	0.55 ± 0.01
Economic damage coefficient	0.50 ± 0.01	0.60 ± 0.01	0.49 ± 0.01	0.58 ± 0.01	0.43 ± 0.01	0.62 ± 0.01	0.45 ± 0.01	0.62 ± 0.01	0.55 ± 0.01	0.50 ± 0.01
CDR cost (1st Gt CO_2)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.04 ± 0.00
CDR cost (50th Gt CO_2)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.02 ± 0.00
Mitigation cost (1st Gt CO_2)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Mitigation cost (50th Gt CO_2)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
TCRE	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.02 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.03 ± 0.00

Sobol indices of Total Mitigation (GtCO2)										
Cost Category	**SSP1**		**SSP2**		**SSP3**		**SSP4**		**SSP5**	
	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T
Discount rate	0.00 ± 0.00	0.01 ± 0.00	0.02 ± 0.00	0.03 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.05 ± 0.00
Economic damage coefficient	0.01 ± 0.00	0.06 ± 0.00	0.03 ± 0.00	0.14 ± 0.00	0.01 ± 0.00	0.05 ± 0.00	0.01 ± 0.00	0.08 ± 0.00	0.05 ± 0.00	0.15 ± 0.01
CDR cost (1st Gt CO_2)	0.25 ± 0.01	0.27 ± 0.01	0.49 ± 0.01	0.52 ± 0.01	0.55 ± 0.01	0.57 ± 0.01	0.43 ± 0.01	0.45 ± 0.01	0.46 ± 0.02	0.69 ± 0.02
CDR cost (50th Gt CO_2)	0.01 ± 0.00	0.01 ± 0.00	0.03 ± 0.00	0.04 ± 0.00	0.03 ± 0.00	0.04 ± 0.00	0.02 ± 0.00	0.03 ± 0.00	0.02 ± 0.01	0.31 ± 0.01
Mitigation cost (1st Gt CO_2)	0.04 ± 0.00	0.04 ± 0.00	0.05 ± 0.00	0.07 ± 0.00	0.08 ± 0.01	0.09 ± 0.00	0.06 ± 0.01	0.07 ± 0.00	0.02 ± 0.00	0.03 ± 0.00
Mitigation cost (50th Gt CO_2)	0.00 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.02 ± 0.00	0.02 ± 0.00	0.03 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.03 ± 0.00	0.03 ± 0.00
TCRE	0.62 ± 0.01	0.64 ± 0.01	0.24 ± 0.01	0.26 ± 0.01	0.24 ± 0.01	0.25 ± 0.00	0.38 ± 0.01	0.39 ± 0.01	0.12 ± 0.01	0.17 ± 0.01

Sobol indices of Total Removal (GtCO2)										
Cost Category	**SSP1**		**SSP2**		**SSP3**		**SSP4**		**SSP5**	
	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T	S_1	S_T
Discount rate	0.00 ± 0.00	0.01 ± 0.00	0.02 ± 0.00	0.02 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.05 ± 0.00
Economic damage coefficient	0.01 ± 0.00	0.07 ± 0.00	0.02 ± 0.00	0.13 ± 0.00	0.01 ± 0.00	0.05 ± 0.00	0.01 ± 0.00	0.08 ± 0.00	0.05 ± 0.00	0.16 ± 0.01
CDR cost (1st Gt CO_2)	0.29 ± 0.01	0.31 ± 0.01	0.45 ± 0.01	0.49 ± 0.01	0.58 ± 0.01	0.60 ± 0.01	0.45 ± 0.01	0.47 ± 0.01	0.49 ± 0.01	0.78 ± 0.03

CDR cost (50th Gt CO_2)	0.01 ± 0.00	0.01 ± 0.00	0.03 ± 0.00	0.04 ± 0.00	0.03 ± 0.00	0.04 ± 0.00	0.02 ± 0.00	0.03 ± 0.00	0.02 ± 0.01	0.32 ± 0.02
Mitigation cost (1st Gt CO_2)	0.04 ± 0.00	0.05 ± 0.00	0.05 ± 0.00	0.06 ± 0.00	0.08 ± 0.01	0.10 ± 0.00	0.06 ± 0.01	0.08 ± 0.00	0.02 ± 0.00	0.03 ± 0.00
Mitigation cost (50th Gt CO_2)	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.04 ± 0.00	0.02 ± 0.00	0.04 ± 0.00	0.01 ± 0.00	0.03 ± 0.00	0.03 ± 0.00	0.03 ± 0.00
TCRE	0.56 ± 0.01	0.59 ± 0.01	0.29 ± 0.01	0.30 ± 0.01	0.20 ± 0.01	0.21 ± 0.00	0.35 ± 0.01	0.36 ± 0.01	0.07 ± 0.01	0.12 ± 0.00

Values shown as mean ± standard deviation. S_1 = first-order Sobol index; S_T = total-order Sobol index. Three scenarios are analysed: Total Cost (sum of mitigation, carbon dioxide removal and temperature-dependent climate damages), Total Mitigation (emissions reduction volume), and Total Removal (carbon dioxide removal volume). Higher index values indicate greater parameter influence on model output variance.

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