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To cite this article: Thomas Bossy *et al* 2024 *Environ. Res.: Climate* **3** 025005

IOP Publishing Environ. Res.: Climate 3 (2024) 025005 https://doi.org/10.1088/2752-5295/ad34a8

ENVIRONMENTAL RESEARCH
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RECEIVED
21 October 2023

REVISED
26 February 2024

ACCEPTED FOR PUBLICATION
15 March 2024

PUBLISHED
2 April 2024

PAPER

Least-cost and 2 °C-compliant mitigation pathways robust to physical uncertainty, economic paradigms, and intergenerational cost distribution

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Keywords: mitigation costs, inertia, Paris Agreement, IAM, simple climate models

Supplementary material for this article is available online

Abstract

Each run of an integrated assessment models produces a single mitigation pathway consistent with stated objectives (e.g. maximum temperature) and optimizing some objective function (e.g. minimizing total discounted costs of mitigation). Even though models can be run thousands of times, it is unclear how built-in assumptions constrain the final set of pathways. Here we aim at broadly exploring the space of possible mitigation scenarios for a given mitigation target, and at characterizing the sets of pathways that are (near-)optimal, taking uncertainties into account. We produce an extensive set of CO_2 emission pathways that stay below 2 °C of warming using a reduced-form climate-carbon model with a 1000 different physical states. We then identify 18 sets of quasi 'least-cost' mitigation pathways, under six assumptions about cost functions and three different cost minimization functions embarking different visions of intergenerational cost distribution. A first key outcome is that the absence or presence of inertia in the cost function plays a pivotal role in the resulting set of least-cost pathways. Second, despite inherent structural differences, we find common pathways across the 18 combinations in 96% of the physical states studied. Interpreting these common pathways as robust economically and in terms of intergenerational distribution, we shed light on some of their characteristics, even though these robust pathways differ for each physical state.

1. Introduction

Climate change mitigation requires careful planning and strategic decision-making. Integrated assessment models (IAMs) have emerged as a crucial tool for informing these decisions, providing insights into the potential costs and benefits of different mitigation strategies [1–3]. However, the use of IAMs is not without limitations as they often rely on simplified representations of complex economic and climatic processes, leading to significant structural uncertainties in their projections [4, 5].

While previous studies [6–8] have acknowledged and explored these limitations and uncertainties, a significant gap remains in our understanding of how they interact with—and influence—the identification of least-cost or near-optimal pathways. In particular, the impact of assumptions on mitigation costs and on the objective functions to minimize to select pathways remains under-studied [9]. Older studies have already compared the effects of structural assumptions such as inertia or induced technological change in the form of learning by doing (LBD) or R&D [10–12]. However, these studies only look for optimal pathways in the context of cost-effective or cost-benefit analyses. We are not aware of any study that analyzes a full set of ex ante mitigation pathways and aims to identify not just one optimal pathway, as robust as it can be with sensitivity tests, but a set of least-cost pathways to highlight similarities between different structural assumptions on the cost functions. The objective of this study is to explore how different cost function paradigms and different choices of objective functions used for minimization affect the identification of least-cost mitigation pathways in different representations of Earth system physics to account for physical uncertainty.

We use a backward approach to back-calculate a large ensemble of global CO_2 emission scenarios based on temperature and atmospheric CO_2 concentration pathways that correspond to an interpretation of Paris Agreement goals:[5] staying below +2 °C and asymptotically reaching +1.5 °C in the very long term. We identify least-cost pathways in this large ensemble that are common to different mitigation cost function [5, 13] and that do not rely on the choices of objective functions to minimize [14, 15]. Two of these objective functions are chosen to define least-cost pathways on the entire timeframe while the third objective function is defined to minimize intergenerational cost sharing. Overall, we aim to identify robust and equitable set of CO_2 emission pathways consistent with the 2 °C temperature target considering physical uncertainty through a 1000 representations of the physical state of the world.

2. Methods

2.1. Generation of pathways meeting Paris Agreement

We start by defining an ensemble of temperature and CO_2 atmospheric concentration pathways that are generated based on analytic formulations detailed in supplementary materials (figure 1, step 1). Overall, we provide about 2000 CO_2 ex-ante temperature scenarios, all of which remain below 2 °C, and associated CO_2 concentration scenarios. We then back-calculate corresponding CO_2 emission and non-CO_2 radiative forcing (non-CO_2 RF) pathways (figure 1, step 2). We assume that it is impossible to have more emission reduction than in the most ambitious scenario from the AR6 scenario database. Therefore, if CO_2 emissions fall below the most mitigation-intensive trajectories, without the use of negative emission technologies, from the AR6 scenarios [16], we attribute the gap to carbon dioxide removal (CDR). The back-calculation of emission pathways is performed by Pathfinder v1.0.1 [17], a reduced-complexity carbon-climate model. The model parameters are based on complex climate models from CMIP6 and were calibrated by Bayesian inference [18] using observations and assessed values from the latest IPCC report. To account for physical uncertainty, the model is run under 1000 different sets of model parameters representing the physics of the Earth system, hereafter configured with parameters drawn from the posterior probability distributions resulting from the Bayesian calibration (figure 1, step 2).

Our ex-ante method for generating temperature and CO_2 atmospheric concentration input trajectories does not reflect socioeconomic considerations (supplementary materials). To eliminate pathways totally unrealistic socioeconomically we eliminate scenarios where CDR exceeds 37 $GtCO_2$ yr^{-1}, although it remains a very elusive upper bound [19]. We also remove scenarios where non-CO_2 RF drops below the AR6 scenarios envelope [16]. All pathways are consistent with mitigation of non-CO_2 forcers as well as projections of CDR deployment in AR6. To avoid retaining pathways being realistic only because of a particular Earth system physics in Pathfinder, we ensure that the two conditions above are met in at least 80% of the 1000 configurations. Unlike most IAMs [4], we do not look for one cost-optimal pathway, but for a set of near-optimal pathways derived from a much larger ensemble of possible emission pathways.

2.2. Range of mitigation cost functions

Aggregated cost functions have been developed by different modeling teams. Costs are typically represented by a power law of abatement, at times also including a linear term. Some also include terms dependent on abatement speed to capture system inertia while others include terms with cumulated abatement to capture accumulation mechanisms such as induced technological change [9].

Our objective is to test structural assumptions on the costs. To map the different conceptual possibilities found in the literature, we use six mitigation cost functions. The first function represents costs through a non-linear power law on the abatement level. This function also represents technological with an exogenous discounting term depending on the time. The second function uses the same power law as the first function, but the representation of the technological change differs as it is now endogenous as it no longer is a function of time but a function of cumulated past emissions in order to model a form of LBD. The third functional form comes back to exogenous technological and keeps the power law on abatement but add a quadratic

[5] The overarching goal of Paris Agreement is to hold 'the increase in the global average temperature to well below 2 °C above pre-industrial levels' and pursue efforts 'to limit the temperature increase to 1.5 °C above pre-industrial levels.'

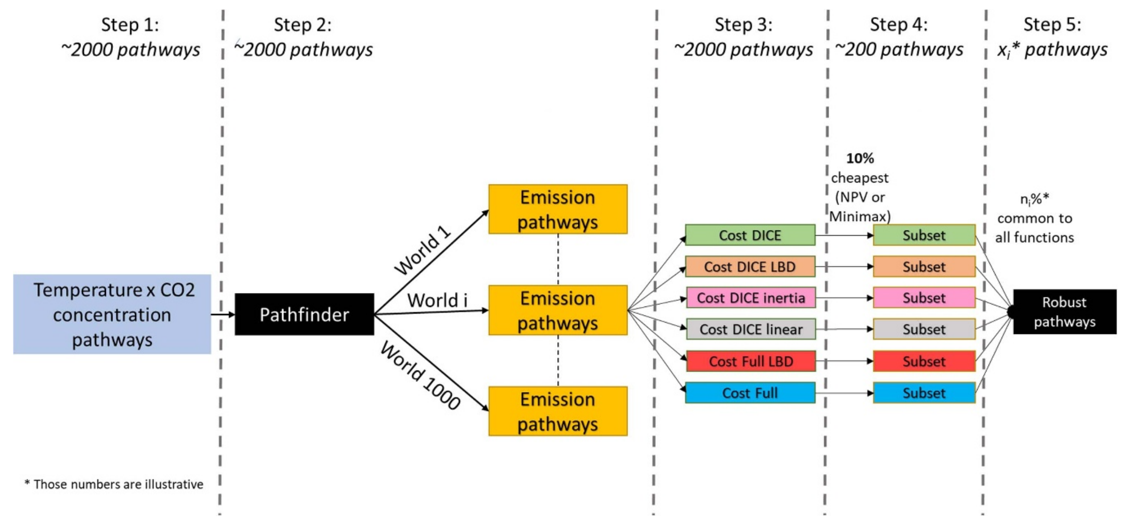

Figure 1. Global framework for defining robust pathways. In step 1, we analytically generate 2 °C-compliant temperature and CO_2 concentration pathways. In Step 2, we use Pathfinder to back-calculate CO_2 emissions and non-CO_2 RF pathways that are compatible with our inputs. In Step 3, we estimate mitigation costs for all our pathways using six different cost functions. In Step 4, we select only the 10% least expensive pathways (according to a chosen objective function). In Step 5, we compare all subsets of least expensive pathways to define robust near-optimal pathways. This process is applied to 1000 physical worlds, each yielding a different percentage of robust pathways.

term depending on the speed of abatement. This is to model the inertia of the system as decarbonizing more rapidly generates higher costs. In the fourth function, instead of adding the inertia term, we add a term that depend linearly on the abatement. Inspired by other models, the addition of this term is the most significant (relatively to the power law) when abatement is below 1 PgC yr^{-1}. Therefore, it allows to force abatement costs in the first years of decarbonization. Finally, the two last functions consider together the power law, the linear and the inertia terms with either exogenous technological change (fifth function) or the endogenous technological change (sixth function).

Mathematically, the functions are derived from five aggregated models with a description easily available: ACC2 [20], DICE [21], PAGE [22], RESPONSE [10] and DICE-PACE [9]. In the most general formulation, mitigation costs can be denoted as $c\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}, \sum a, t\right)$, measured in $10^9\$ \ yr^{-1}$. The first term reflects annually abated emissions relative to a baseline (a in $GtCO_2 \ yr^{-1}$); the second term is the speed of abatement ($\frac{\mathrm{d}a}{\mathrm{d}t}$ in $GtCO_2 \ yr^{-2}$); and the third term is the cumulative sum of abated emissions ($\sum a$ in $GtCO_2$). Costs might also be explicitly time (t)-dependent. We express costs as the product of two functions, $c\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}, \sum a, t\right) = \mathrm{Tech}\left(t, \sum a\right) S\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}\right)$, where $\mathrm{Tech}\left(t, \sum a\right)$ represents technological change. These costs focus on CO_2 mitigation only and do not consider non-CO_2 RF mitigation.

In the literature, technological change can be either endogenous or exogenous. Exogenous or autonomous technological change is represented by an exponentially decreasing factor, typically $\mathrm{Tech}\left(t\right) = \tau^t$, where τ is a discount factor resulting in an annual decrease in mitigation costs by $(1-\tau)^*100\%$ due to external, solely time-dependent innovation.

Endogenous technological change is typically assumed to depend on cumulative past mitigation effort and is represented by a factor $\mathrm{Tech}\left(\sum a\right) = \left(1 + \sigma \sum a\right)^{\mu}$, which captures induced innovation through the process of LBD. Past abated emissions ($\sum a$) are considered an experiential gain that reduces future costs. To account for the initial experience stock (IES) of avoided emissions [22], which reflects the historical learning, or all the emissions abated before 2021, we define $\sigma = \frac{1}{\mathrm{IES}}$ as the reciprocal of IES. It is the sensitivity parameter of the cumulated abatement keeping homogeneity in the equation.

The second term $S\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}\right)$ includes three elements. Firstly, to model the initial behavior of mitigation costs, we introduce a linear element (βa) with β expressed in $\$ \ tC^{-1}$.

Secondly, all examined models incorporate a non-linear element of the form $\left(\alpha - \beta\right) \frac{a^{\theta}}{\theta E^{\theta-1}}$ derived from DICE [21] and employed in RESPONSE [10] and DICE-PACE [9]. Here, E is the exogenous emissions baseline (see below) and α represents the marginal cost for maximum mitigation ($a = E$), which can be interpreted as the current price of the backstop technology (in $\$ \ tC^{-1}$). The cost elasticity, denoted as θ, remains constant.

Finally, the inertia term that penalises the speed of decarbonization is expressed as $\frac{\mathrm{GDP}}{E^{\varphi}}\left(\delta \frac{\mathrm{d}a}{\mathrm{d}t}\right)^{\varphi}$, where GDP is the exogenous GDP baseline (see below) keeping the equation homogenous and δ represents a scaling factor reflecting the transition timescale measured in years. The cost parameter φ, greater than 1, shapes the inertia element.

The non-linear element includes E and the inertia element incorporates E and GDP as multipliers to maintain the homogeneity of the cost function. These terms show the dependency of calculated costs on the chosen baselines. To evaluate the impact of conceptual choices on mitigation costs, not all combinations of these elements are explored. We calculate the costs for each CO_2 emission pathway using six distinct cost functions (figure 1, step 3) that are selected for their relevance, allowing to explore the main conceptual possibilities found in the literature (supplementary materials).

A non-linear element is present under various forms in most of the functions from aggregated IAMs. We choose the *DICE* function as a baseline because it is widely used in the literature [21], and explore three variants with *DICE_LBD*, *DICE_inertia* and *DICE_linear* functions. They were chosen to assess separately the effects of including inertia, of adding a linear element and of adding endogenous technological change into the cost function. This effects have been suggested as important factors in previous studies [9, 10]. Finally, we combine all these new elements in the *Full* and *Full_LBD* functions. Technically, the *DICE* function is defined as:

$$DICE: \; c(a,t) = \tau^t \left[\alpha \frac{a^\theta}{\theta E^{\theta-1}}\right]. \tag{1}$$

Since autonomous technical change and LBD have the same discounting role, it is nearly impossible to calibrate both terms simultaneously, so we choose either one or the other. Therefore, the second functional form is the same as *DICE*, but autonomous technical change is replaced by LBD,

$$DICE\_LBD: \; c\left(a, \sum a\right) = \left(1+\sigma \sum a\right)^\mu \left[\alpha \frac{a^\theta}{\theta E^{\theta-1}}\right]. \tag{2}$$

This conceptual approach takes into account the dynamic realism of emitting systems through induced innovation. It is also possible to maintain an exogenous innovation and introduce an inertia element to the *DICE* form,

$$DICE\_inertia: c\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}, t\right) = \tau^t \left[\alpha \frac{a^\theta}{\theta E^{\theta-1}} + \frac{\mathrm{GDP}}{E^2}\left(\delta \frac{\mathrm{d}a}{\mathrm{d}t}\right)^\varphi\right]. \tag{3}$$

Instead of inertia, we can add a linear element that artificially determines the costs in the first years,

$$DICE\_linear: \; c(a,t) = \tau^t \left[\beta a + (\alpha-\beta)\frac{a^\theta}{\theta E^{\theta-1}}\right]. \tag{4}$$

Each of the first four functions allows each conceptual choice to be assessed separately. We added two more complex functions to examine how mitigation costs behave when we combine several of these conceptual elements, while keeping the distinction between exogenous and endogenous technological innovation,

$$Full: \; c\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}, t\right) = \tau^t \left[\beta a + (\alpha-\beta)\frac{a^\theta}{\theta E^{\theta-1}} + \frac{\mathrm{GDP}}{E^2}\left(\delta \frac{\mathrm{d}a}{\mathrm{d}t}\right)^\varphi\right] \tag{5}$$

$$Full\_LBD: c\left(a, \sum a, \frac{\mathrm{d}a}{\mathrm{d}t}\right) = \left(1+\sigma \sum a\right)^\mu \left[\beta a + (\alpha-\beta)\frac{a^\theta}{\theta E^{\theta-1}} + \frac{\mathrm{GDP}}{E^2}\left(\delta \frac{\mathrm{d}a}{\mathrm{d}t}\right)^\varphi\right]. \tag{6}$$

2.3. Calibration

To calibrate the parameters of the six cost functions in equations (1)–(6), we employ data from the AR6 Scenario Explorer database [16]. Process-based IAMs utilize numerous metrics to derive mitigation costs [23]. These metrics encompass GDP loss, consumption loss, marginal costs of the energy system, marginal energy investments, or carbon price, serving as proxies for mitigation costs. Consequently, directly comparing mitigation costs with the IAM database outputs [16] raises challenges, as the reference or baseline values used to estimate costs are not always explicitly provided for each metric, and complete metric values are not available for all scenarios.

Therefore, for scenarios that can be mapped to a consistent 'baseline' scenario, we calculate the GDP loss and interpret it to be equivalent to the mitigation cost. However, the six cost functions aim to represent several processes that may not have been explicitly considered in IAM scenarios. Furthermore, the functional forms contain numerous terms and parameters without sufficient constraints to effectively replicate costs from complex models. Thus, instead of striving for exact replication of each model's behavior, we opt for a rough calibration approach based on three target years in 2030, 2050, and 2100. All functions are calibrated simultaneously on these three target years. These years were chosen because they are commonly used reference years in IPCC reports [24, 25] and they allow to constrain our functions on the short-, mid- and long-term. Our primary objective is to obtain estimates that provide a realistic order of magnitude compared to the AR6 models' ensemble rather than a precise model replication. Consequently, we calibrate the functional forms simultaneously for all models and scenarios.

In total, there are eight unknown parameters (φ, θ, μ, σ, α, β, δ, τ), with up to seven parameters within the same cost function representation. To improve the calibration, we reduce the degrees of freedom by fixing all parameters except the two that are common to all cost functions, α and θ, and define the remaining parameters based on literature values. In the supplementary materials, we also present an alternative calibration method with more degrees of freedom and highlight its limitations through comprehensive testing. We select $\mu = -2$ and $\varphi = 2$ as the shape parameters [9, 10, 22]. For the sensitivity parameters, based on existing models and literature [10, 21, 22], we set $\sigma = 1.4\ 10^{-4}\ \mathrm{GtCO_2^{-1}}$, $\beta = \$136\ \mathrm{tCO_2^{-1}}$, $\delta = 5\ \mathrm{yr}^{-1}$ and $\tau = 0.995$ (supplementary materials).

We also propose an alternative route, where the two shape parameters were fixed, but with sensitivity parameters calibrated (supplementary materials). This permits up to four free parameters simultaneously, leading to the negation of some of the terms of the cost functions. Therefore, such an alternate calibration unveils the most suitable terms for representing process-based costs, providing insights into the dynamics modeled by process-based IAMs, at the cost of eliminating some of the conceptual terms we investigated in our study. For instance, we found that inertia is unnecessary to emulate these costs, indicating that complex IAMs might not adequately model it.

Since the research question focuses on the structure of the cost function, we are only interested in functional uncertainty and not parametric uncertainty, which justifies the 'constrained' calibration with only two free parameters and a unique calibration for all models without a systematic sensitivity analysis of the parameters.

2.4. GDP and CO_2 emissions baseline

The emission scenarios we develop extend to the year 2300. Yet AR6 scenarios only extend to the year 2100 [16]. To overcome this challenge, we incorporate the projections proposed by Rennert and colleagues [26], which leverage expert assessments to project long-term GDP and CO_2 emissions until 2300. Therefore, we are able to calculate and compare costs until 2300. We describe the implementation of this baseline in supplementary materials and in figure S1.

2.5. Definition of near-optimal and robust pathways

In this study, we define a pathway as near-optimal for one functional form of the cost function and for one of the 1000 configurations if it falls within the 10% 'least expensive' trajectories in the ensemble produced by Pathfinder (figure 1, Step 4, the choice of 10% is discussed in the supplementary materials). We define two types of objective functions for this purpose.

First, we aggregate costs over time by computing the net present value (NPV) for the period from 2021 to 2300, using a discount rate of 4% in agreement with existing literature [21]. This is a standard method [21, 22] focusing on absolute total cost. If we used the most standard discount rate, this choice is the subject a longstanding debate [14, 15] partly focused on the rate of pure time preference in the Ramsey equation [27]. As an alternative we also considered a NPV without discounting in supplementary materials.

Second, we compute the maximum GDP-share of mitigation costs over the period from 2021 to 2300 for each pathway and therefore minimize the max as objective function. We call this the 'max' approach, recognizing that this is different from the minimax regret method used in IAMs to account for parameter uncertainty [28]. The max method ensures that no single generation bears disproportionately high costs relative to others for the sake of minimizing overall NPV. The main difference with more conventional NPV approaches is the fact that the max assumes that transfers between generations are impossible [29, 30]. The underlying idea is that a policymaker that applies the 'max' criterion chooses a policy that minimizes the cost of the worst-off generation [30–32]. Therefore, that approach ensure to avoid temporary spikes in mitigation costs that would penalize heavily one generation relative to the immediately adjacent ones, as such spikes might become politically infeasible for the generation that is 'sacrificed'. However, such criteria may be less justified for distant generations, especially if some are much richer than others [29, 30].

Following previous work [33], we introduce a third objective function called $\mathrm{NPV_{Diff}} = \left|\frac{\mathrm{NPV1-NPV2}}{\mathrm{NPV2}}\right|$ as, as follows. Net discounted mitigation costs in 2020 are computed both for the current generation (arbitrarily set at 2021–2060,NPV1), and the next one (2061–2100, NPV2). We calculate the difference of the NPVs and normalize using NPV2. The objective is to minimize $\mathrm{NPV_{Diff}}$. A $\mathrm{NPV_{Diff}}$ of zero means that each 'generation' contributes the same discounted amount to mitigation (the gross amount is higher for generation 2, since

NPV2 is discounted by 40 more years than NPV1). A positive NPV_{Diff} implies that one generation has higher discounted costs than the other. Although the 40 year cutoff is arbitrary, this criteria aims at providing an indicator of intergenerational cost distribution in a World where arbitrage is more difficult to achieve within than across generations (computing a NPV across all periods assumes arbitrage is equally easy across or within generations).

The combinations of three types of objective functions (NPV, max and $\mathrm{NPV}_{\mathrm{Diff}}$) and six cost function definitions, result in 18 different subsets of near-optimal pathways. 'Robustness' is defined based on the intersection of the resulting subsets, i.e. pathways which belong to the intersection of, two to all 18, subsets are considered 'robust'. We introduce a robustness score defined as the ratio of the number of robust pathways to the size of subsets (10% of the ensemble's size).

Pathways that are robust with respect to variations in cost functions but using the same type of objective function are labeled 'robust to NPV' and 'robust to max', depending on the type of objective function. The term 'generationally robust' is assigned to a pathway that exhibits near-optimality regardless of the employed cost function and with $\mathrm{NPV}_{\mathrm{Diff}}$ as objective function for minimization. Moreover, we call 'economically robust' near-optimal pathways which are robust with respect to variations in cost functions and the first two objective functions (NPV and max). Finally, pathways that belong to the intersection of all 18 subsets are called 'economically and generationally' robust.

3. Results

3.1. Calibration results

The calibration process is evaluated for the three target years (2030, 2050, and 2100). Figure 2 compares the costs obtained from six different calibrated cost functions against the AR6 IAMs costs. In 2050 and 2100 demonstrate that all six functions yield similar projections reasonably aligned with the AR6. However, the calibrated functions tend to underestimate costs when mitigation is high, i.e. approaching 10% of GDP, while overestimating costs when mitigation is low (figure S2). Figure 2 presents the cost distribution in the target years and differentiates scenarios into categories from C1 (high mitigation) to C6 (low mitigation) defined in the IPCC's working group III report [34] (detailed in figure S7). In 2050 and 2100, all functional forms of cost estimation remain within the uncertainty range of the IPCC AR6 costs [16]. Nevertheless, in 2050, there is a slight tendency for all functional forms to overestimate costs associated with the high mitigation scenarios (C1 and C2 scenarios). In 2100, regardless of the scenario classification (C1 to C6), all functional forms yield similar cost estimates, with a slight overestimation observed for the C5 scenarios.

Cost estimates associated with the functions incorporating inertia (*DICE_inertia*, *Full*, *Full_LBD*) exhibit significantly higher costs than expected by IPCC in 2030. Figure 2 provides further evidence that functions incorporating inertia consistently yield cost estimates well above the range provided by the IPCC for all scenarios, whereas the functions without inertia (*DICE, DICE_LBD, DICE_linear*) align more closely with the IPCC estimates. This discrepancy is particularly pronounced for the scenarios demanding more stringent mitigation measures, namely C1, C2, and C3. The introduction of the inertia element with a transition time scale (δ) of 5 years, which is faster than what is typically found in the literature, leads to a short-term overestimation of costs. This outcome is expected due to the underestimation of inertia in the process-based IAMs employed in the AR6 database [9]. Interestingly, in the presence of the inertia element, the inclusion of the linear element in the cost functions (*Full* and *Full_LBD*) further overestimates the costs compared to the functions without this linear element (*DICE_inertia*). Conversely, the linear element alone (*DICE_linear*) does not contribute to higher cost estimates.

The calibrated values of the parameters in table 1 demonstrate that θ, the shape parameter or elasticity of the power law, is independent of the function used to estimate technological change (endogenous or exogenous). Regardless of whether LBD is included, the same functional forms yield very similar calibrated values for θ. It is observed that the number of terms included in the cost function determines the value of θ. When only the power law is considered, θ is approximately 2 (*DICE* and *DICE_LBD*). Introducing the power law alongside another term increases θ to approximately 3.5 (*DICE_inertia* and *DICE_linear*). Finally, incorporating all three terms (*Full* and *Full_LBD*) in the cost function yields a value of θ around 5.5. The value of α, the sensitivity parameter of the power law, remains stable between \$640/tCO_2 to \$880/tCO_2. It is in agreement with other similar model's parametrisation (supplementary materials). The behavior of θ is explained by the need to compensate the addition of the inertia and linear terms to $S\left(a, \frac{\mathrm{d}a}{\mathrm{d}t}\right)$. These terms have higher values on short-term costs in 2030 than on mid- or long-term costs in 2050 or 2100. Therefore, the weight of the power law must be diminished particularly in 2030. As a/E is relative abatement, it is by construction smaller on short-term and a high θ reduces significantly the term's value. When a is getting closer to E for 2050 and 2100, the power law is less affected by a higher elasticity and the weight of the inertia

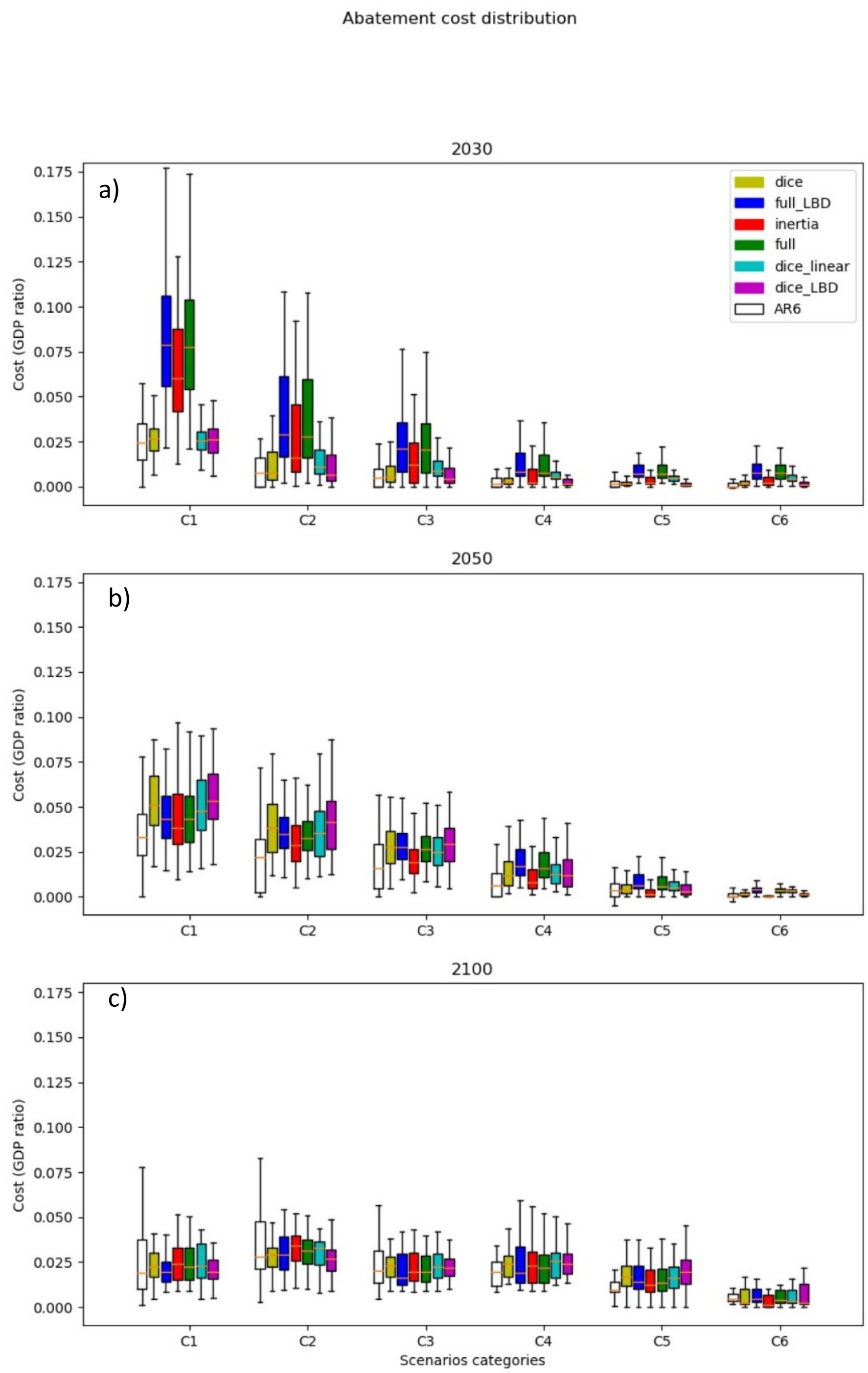

Figure 2. Distribution of mitigation costs from AR6 (white boxes) compared to the six calibrated cost functions (colored boxes) for scenarios across six categories ranked from high to low mitigation scenarios (C1 to C6). Costs are calculated and calibrated on three crossing points in 2030 (panel (a)), 2050 (panel (b)), and 2100 (panel (c)).

and linear terms are reduced. Hence, the value of θ is adjusted in the calibration to match AR6 scenarios costs in 2030.

3.2. Selection of economically robust pathways

When applying the NPV approach, the choice of the cost function seems to exert minimal influence: 78% (median robustness score) of the near-optimal pathways are common across all cost functions (figure 3(a)).

Figure 3(b) shows that the intersection of the subsets of cost function with inertia (*DICE_inertia, Full, Full_LBD*) and max as objective function entails 98% of all near-optimal pathways, while this number is 92% for the subsets of cost functions without inertia (*DICE, DICE_LBD, DICE_linear*). The intersection of all max subsets entails only 55% of scenarios, the discriminatory factor is clearly whether or not inertia is

Table 1. Calibration of the parameters of the mitigation cost functions. α represents the marginal cost for maximum mitigation, which essentially represents the current price of the backstop technology. The cost elasticity is denoted as θ.

	α	θ
DICE	$636/tCO$_2$	1.93
DICE_LBD	$792/tCO$_2$	2.17
Full	$661/tCO$_2$	5.46
Full_LBD	$807/tCO$_2$	5.74
DICE_inertia	$881/tCO$_2$	3.84
DICE_linear	$742/tCO$_2$	3.35

Table 2. (a) Percentage of near-optimal pathways robust for $\max_f$ and two cost functions. The max objective function minimizes the maximum relative cost (as a percentage of GDP) across pathways, without discounting. (b) Percentage of near-optimal pathways robust for NPV and two cost functions. The NPV criterion minimizes the net present value on the period 2021–2300. (c) Percentage of near-optimal pathways robust for NPV_{Diff} and two cost functions. The NPV_{Diff} criterion minimizes the difference of net present value between two generations spanning on the periods 2021–2060 and 2061–2100.

Max						
	DICE	Full_LBD	DICE_inertia	Full	DICE_linear	DICE_LBD
DICE	100%	62%	61%	61%	93%	93%
Full_LBD		100%	98%	98%	57%	57%
DICE_inertia			100%	100%	55%	56%
Full				100%	55%	56%
DICE_linear					100%	96%
DICE_LBD						100%
NPV						
	DICE	Full_LBD	DICE_inertia	Full	DICE_linear	DICE_LBD
DICE	100%	83%	83%	83%	91%	93%
Full_LBD		100%	98%	98%	81%	83%
DICE_inertia			100%	100%	81%	83%
Full				100%	81%	83%
DICE_linear					100%	96%
DICE_LBD						100%
NPV_{Diff}						
	DICE	Full_LBD	DICE_inertia	Full	DICE_linear	DICE_LBD
DICE	100%	47%	47%	47%	68%	84%
Full_LBD		100%	99%	99%	38%	33%
DICE_inertia			100%	100%	38%	33%
Full				100%	38%	33%
DICE_linear					100%	58%
DICE_LBD						100%

considered by cost functions. In other words, about 40% of the scenarios that are near-optimal considering inertia are likely to be non-optimal when inertia is not considered. This result puts the debates on the linear or technological change elements into perspective and would argue for a comparison only between *DICE* and *DICE_inertia* (table 2).

Pathways economically robust to the choice of both the cost function and objective function (between NPV and max), constitute 54% of all near-optimal pathways. Therefore, almost all pathways robust to max are also robust to NPV, as depicted in figure 3(c) (inferred from 43% robustness to NPV and max only plus 11% of robustness to NPV, NPV_{Diff} and max).

3.3. Impact of the objective function on inter-generational cost distribution

We find that 24% of the near-optimal pathways are robust to the NPV difference (i.e. generationally robust). The choice of the cost function has a large impact, and the key distinguishing feature is inertia. On figure 3(d) we divide the cost functions between the ones with inertia and the ones without. We find a generational robustness scores of 99% for functions with inertia meaning that near-optimal pathways are almost identical for the three functions. Conversely, the generational robustness is only 57% for functions without inertia.

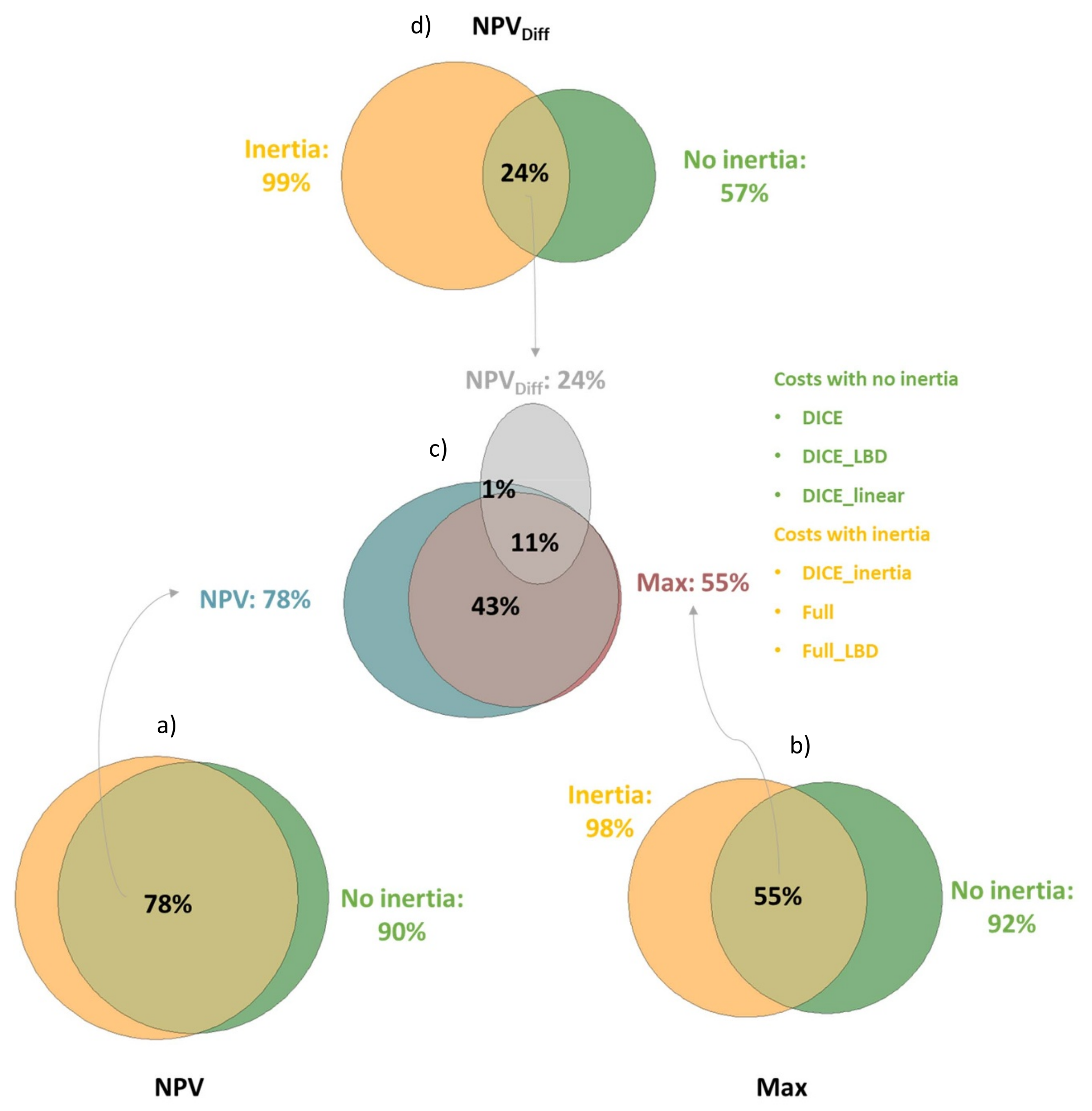

Figure 3. Venn diagrams showing the robustness score for near-optimal pathways that are robust to max, NPV and NPV_{Diff} (panel (a)). Panels (b)–(d) decompose the robustness score for these robust pathways among cost functions that do or do not account for inertia. The intersection spaces of the circles in panels (b)–(d) correspond to the size of ellipses in panel (a). All robustness scores correspond to the median value across all Pathfinder's configurations.

Figure 3(c) shows that there is overlap between pathways robust to NPV, max and NPV_{Diff}. Indeed, 12% of the near-optimal pathways show robustness to NPV and NPV_{Diff}. 11% of the near-optimal pathways show robustness to NPV, max, and NPV_{Diff} and can be qualified as economically and generationally robust.

Figure 4 proves that inertia has an impact on intergenerational cost distribution showing that optimal pathways are more equitable if inertia is considered. Indeed, the intersection of subsets considering inertia in the cost function for the three objective functions gives a robustness score of 43%. On the other hand, the intersection of subsets not considering inertia in the cost function for the three objective functions only gives a robustness score of 15%. Therefore, we observe that using a cost function with inertia implies finding pathways that are minimizing the mitigation costs and the difference between the current and future generation.

Generationally robust pathways minimize the difference of NPV between the present and future generations. Yet, minimizing NPV_{Diff} (defined as $NPV_{Diff} = \frac{NPV1-NPV2}{NPV2}$) does not mean its value is close to 0. On figure S3, we show the distribution of NPV_{Diff} values for generationally robust near-optimal pathways. On one hand, cost functions without inertia are centered on zero and NPV_{Diff} spreads between -0.3 and 0.3. On the other hand, cost functions with inertia shifts costs significantly toward the first generation as NPV_{Diff} is centered on 60. Because costs are expressed in \$2020 for both generations, and thus taking discounting into account, it means that when inertia is considered the present generation would face costs around 10

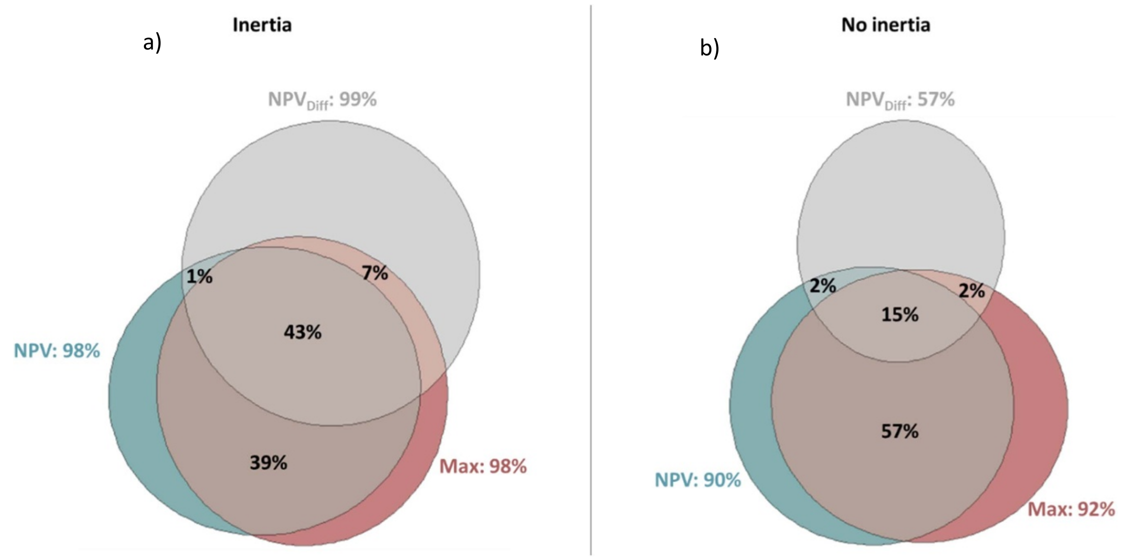

Figure 4. Venn diagrams showing the intersection of subsets of near-optimal pathways for three objective functions (max, NPV and NPV_{Diff}) and using only cost functions with inertia (*DICE_inertia, Full, Full_LBD*) (panel (a)). Panel (b) shows the intersection of subsets of near-optimal pathways for three objective functions (max, NPV and NPV_{Diff}) and using only cost functions without inertia (*DICE, DICE_LBD, DICE_linear*). All robustness scores correspond to the median value across all Pathfinder's configurations. The size of ellipses in panel (a) corresponds to yellow ellipses in Figure 3. The size of ellipses in panel (b) corresponds to green ellipses in figure 3.

times more expensive than the future generation. This difference is explained by our cost-effective approach because all pathways must remain below 2 °C, requiring early and strong mitigation efforts before 2060 leading to high inertial costs.

3.4. The role of physical parameters on defining near-optimal pathways

The physical uncertainties (see Methods) have been accounted for as we have reported so far the median robustness scores across our 1000 potential worlds. The distribution across configurations of four critical robustness scores is shown in figure 5. Figure 5(a) focuses on pathways robust to max, figure 5(b) on pathways economically robust, figure 5(c) on pathways generationally robust and figure 5(d) on pathways generationally and economically robust. These distributions underscore that the six cost functions are able to lead to near-optimal pathways robust to various objective functions in the vast majority of the configurations. In figure 5, there are about 1% of the configurations that do not find near-optimal pathways generationally robust (figure 5(c)) and about 4% not finding economically and generationally robust pathways (figure 5(d)). The distributions do not exhibit significant skewness, justifying the use of the median.

For enhanced understanding of these distributions, their correlation with certain diagnostic metrics on the model's climate and carbon cycle are considered (figure 6). Notably, a correlation emerges between the Equilibrium Climate Sensitivity (ECS [35]) or the Transient Climate Response to Emissions (TCRE [36]) and the robustness score of near-optimal pathways that are economically robust. High TCRE or ECS means that the Earth system is more sensitive to anthropogenic emissions and stronger mitigation is needed to remain below 2 °C. The negative correlation signifies that a heightened ECS or TCRE in the model corresponds with lower agreement between the cost functions used to define near-optimal pathways. Therefore, a configuration featuring a lower TCRE or ECS permits smoother mitigation scenarios, attenuating the impact of inertia on costs. Since inertia is the decisive factor when evaluating the robustness score of near-optimal pathways economically robust or only robust to max, a diminished inertia impact logically fosters greater consensus among cost functions and thus a larger robustness score.

We find no significant correlation between physical parameters of the model and the robustness score for generationally or economically and generationally robust pathways.

3.5. Influence of robustness criteria on the envelope of near-optimal pathways

We set thresholds for the ability of physical configurations to identify economically and generationally robust pathways. Suitable thresholds may diverge based on stakeholder groups and risk attitudes [37]. We propose a focus on two: the median (i.e. the 50th percentile), that we have already extensively used, and the 1st percentile of configurations that locate the smallest robustness score of economically and generationally robust pathways (red line on figure 5(d)). Looking at the 1st percentile is our equivalent of the 'worst

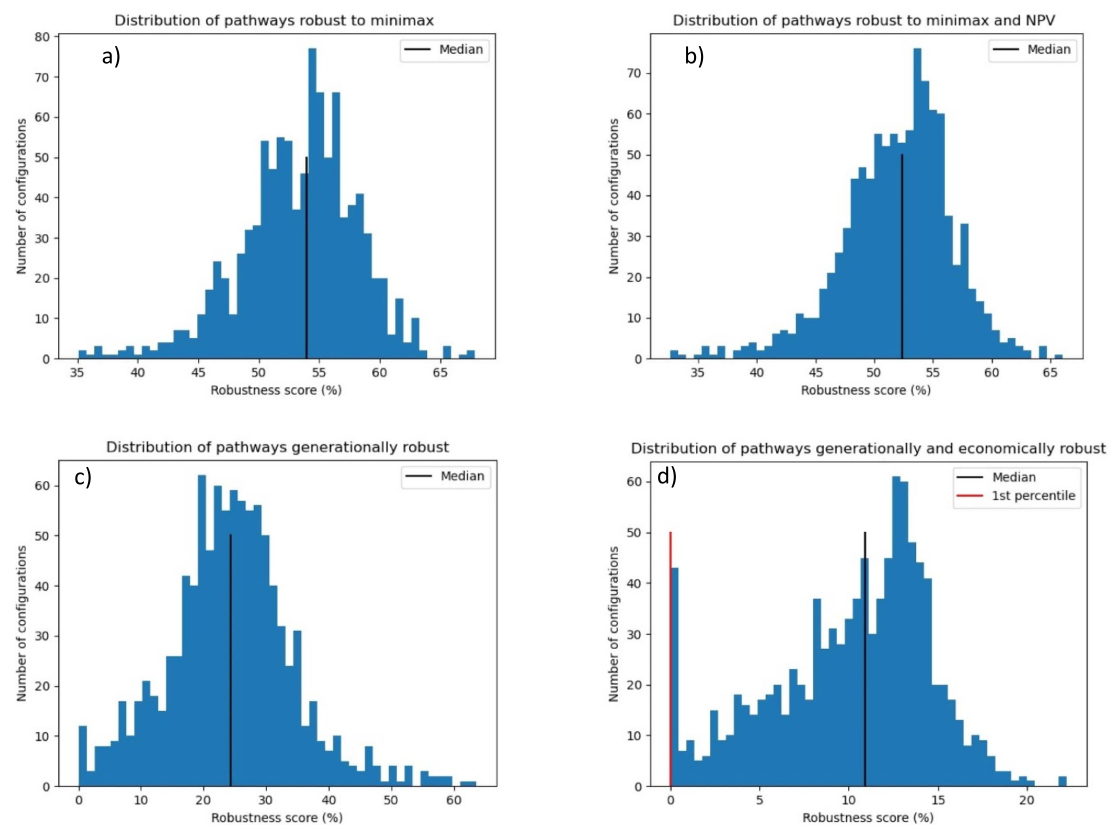

Figure 5. Distribution of the robustness score for near-optimal pathways robust to max (panel (a)), max and NPV (panel (b)), NPV_{Diff} (panel (c)), and NPV_{Diff}, NPV and max (panel (d)). The black line gives the median value of these distributions. In panel (d), the red line gives the 1st percentile of the configuration with the least economically and generationally robust pathways.

possible physical world' and has been chosen because it corresponds to a case which is *exceptionally unlikely* to occur according to IPCC [38].

To explore how the different definitions of robustness influence the selection of pathways, we juxtapose the envelopes of near-optimal pathways generated by different definitions of robustness. Figure 7 illustrate how the envelope of near-optimal pathways reduces when adding conditions for robustness and for the 50th (figure 7(a)) and 1st percentiles (figure 7(b)) of the least robust configurations. On both panels, the widest envelope corresponds to all the 2 °C compatible pathways. In this non-optimized case, certain pathways deploy up to 37 $GtCO_2$ yr^{-1} of CDR prior to 2050 and other pathways remain below 2 °C with late emission peak and mitigation. The second widest envelope correspond to near-optimal pathways employing only NPV as the objective function and *DICE* as the cost function (denominated as *DICE*-NPV). Pathways from this envelope use up to 33 $GtCO_2$ yr^{-1} from CDR, although this maximum deployment happens later than 2100. The third envelope encompass economically robust near-optimal pathways. The most extreme of these scenarios requires around 11 $GtCO_2$ yr^{-1} from CDR slightly before 2100. Ultimately, the most restrictive envelope in figure 7(a) ensures both generational and economic robustness. It covers the lower end of the envelope of economically robust pathways. It implies that earlier net-zero emissions with the use of CDR in the second part of the 21st century is more generationally equitable than pathways aiming for net-zero at the end of the century. As shown in figure 5(d), there are no near-optimal pathways economically and generationally robust for the 1st percentile of configurations. Therefore, the last envelope disappears in figure 7(b). Overall, irrespective of the physical configuration, extreme pathways featuring early and severe, or delayed mitigation vanish when economic robustness is incorporated. Conversely, economically and generationally near-optimal pathways, when they exist, appear to advocate a significant early mitigation allowing to delay the deployment of 11 $GtCO_2$ yr^{-1} of negative emissions after 2100. Further analysis in supplementary materials demonstrates the consistency of these pathways with comparable IPCC's AR6 scenarios.

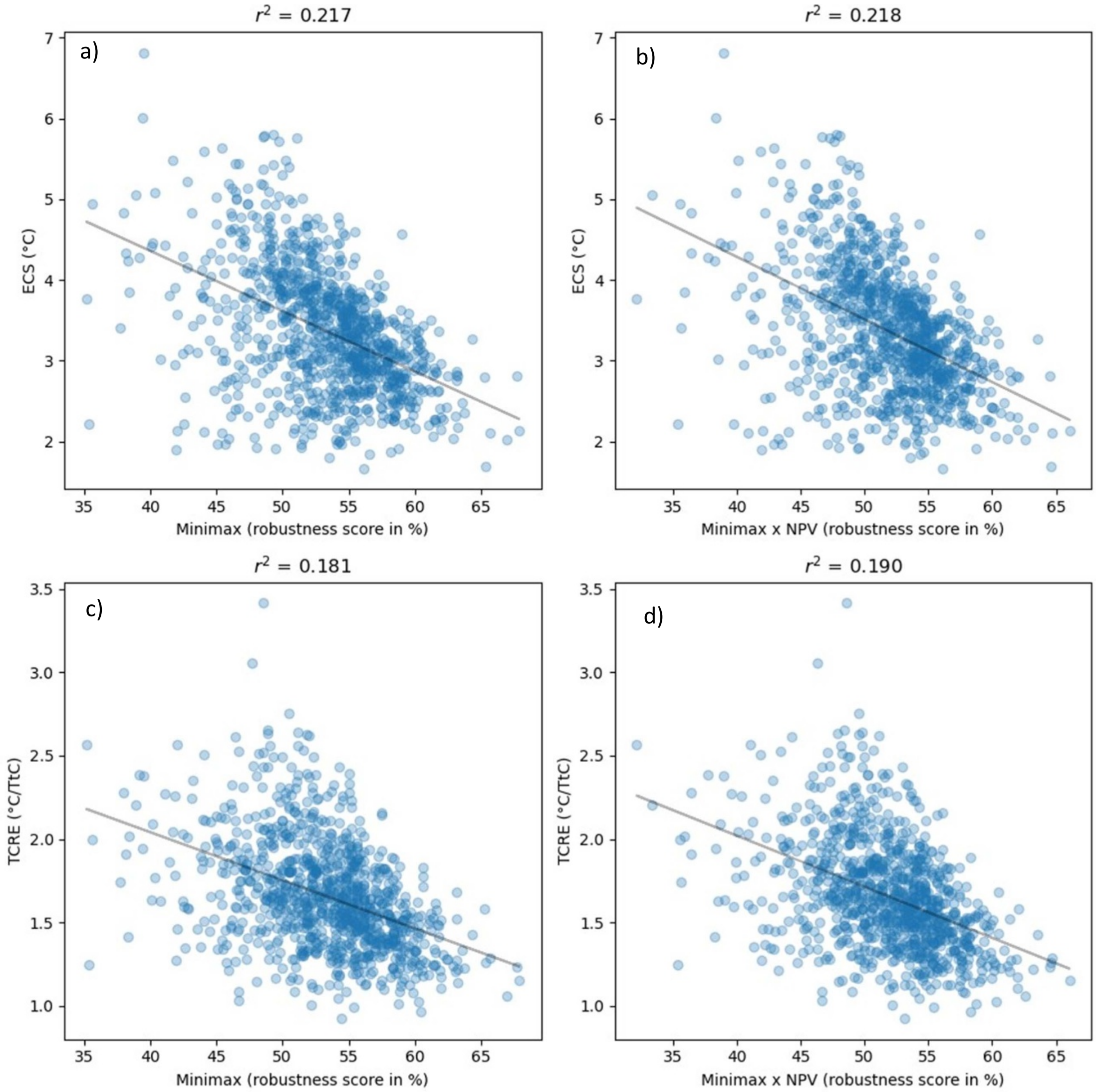

Figure 6. Scatter plots representing the robustness of near-optimal pathways robust to max (panels (a), (c)) or economically robust, i.e robust to max and NPV (panels (b), (d)) in function of the ECS (panels (a), (b)) or the TCRE (panels (c), (d)).

4. Discussion

Process-based IAMs behave very differently depending on the model and the SSP scenario chosen. Some very simple mathematical representations [39] reproduce the marginal abatement costs of particular models and scenarios at the expense of generalization and economic interpretation of the emulator. We prefer to use functions that we can interpret economically at the expense of accuracy. However, our functions remain simplified and global representations. In particular, our aggregate approach does not separate the costs of negative emissions technologies from those of emissions reductions.

The objective function for global costs minimization forms the second choice for calculating mitigation costs that we analyzed. We made deliberate choices in setting the discount rate, a topic extensively debated with well-documented implications of these decisions [28, 40]. A discount rate of 4% is generally acceptable, mirroring the value used in most IAMs, although it generates a strong preference for the present. The max approach does not necessitate a discount rate but is different from an NPV without discounting. To substantiate this distinction, we executed a recalculation of cost estimations and optimizations using a 0% discount rate. In this case, 59% of the near-optimal pathways for the NPV devoid of discounting are robust. Interestingly, this percentage is more aligned with the max approach than with the NPV that incorporates a 4% discounting. Yet, it is worth noting that the NPV with 0% discounting generates fewer economically robust pathways as compared to an NPV with a 4% discount. Thus, it can be effectively inferred that 54% of

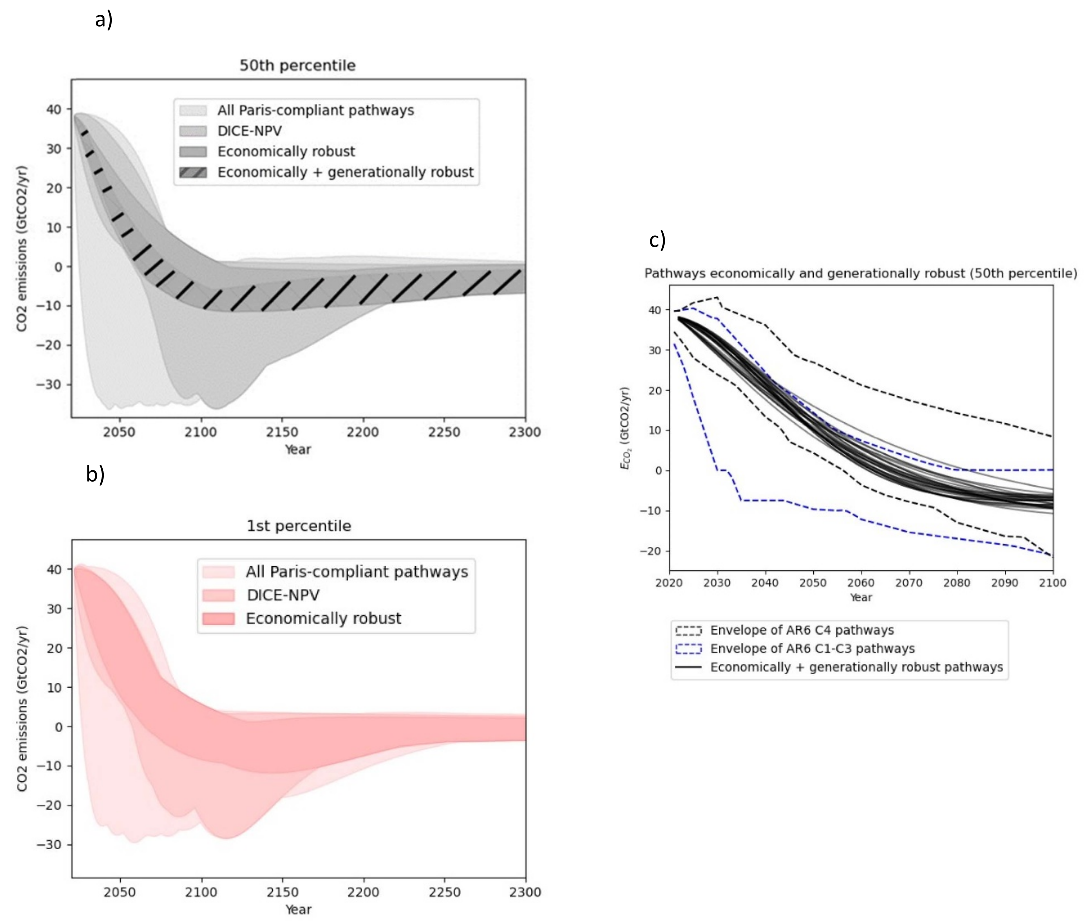

Figure 7. Economically and generationally robust pathways for two Pathfinder configurations corresponding to the 50th (gray) and the 1st (red) percentiles of the distributions of ratios of near-optimal pathways robust to max, NPV and NPV_{Diff}. Shaded areas give the envelopes (from lighter to darker) of (1) all the Paris-compliant pathways calculated by Pathfinder, (2) the near-optimal pathways for *DICE* as a cost function and NPV as a minimization paradigm, (3) the near-optimal pathways economically robust, and (4) the near optimal pathways economically and generationally robust. The envelopes are represented for the 50th percentile on panel (a), and for the 1st percentile on panel (b). Envelope (4) only appears on panel (a) and is hatched. Panel (c) zooms on the period 2020–2100 and shows all economically and generationally robust pathways for both 1st and 50th percentile configurations. Black and blue dashed lines represent the envelope of C4 and C1-C3 AR6 scenarios. Non-CO_2 RF coupled to the CO_2 emission trajectories of panel (c) are shown in figure S6.

near-optimal pathways display robustness under both the max and NPV paradigms incorporating a discount rate. Contrarily, a mere 38% of pathways manifest robustness under both the NPV bereft of any discounting and the max approach (figure S4).

We opted for a cost-effective approach under a constraint of limiting the temperature to below 2 °C to comply with the Paris Agreement. In doing so, we compare pathways that peak at 2 °C in 2100 and tend towards 1.5 °C in 2300 with pathways that asymptotically reach 1.5 °C in 2100. Our cost-effective approach assumes that damages are the same across all emission scenarios meeting that target. This constitutes a potent assumption, especially if we intend to tackle intergenerational cost distribution issues. One could argue that a 2 °C limit is adequate to prevent the most disastrous damages, but the impacts of a 1.5 °C and a 2 °C scenario diverge significantly in terms of costs, population vulnerability, or biodiversity loss [41, 42]. However, our methodology could be applied to any temperature target and hence, remains an insightful tool for identifying and exploring near-optimal scenarios. Further consideration of potential damages and their distribution across generations would be a natural follow-up research.

5. Conclusion

This study has built an extensive ensemble of 2 °C-compatible CO_2 emission scenarios with 1000 different physical representations of the Earth system. This approach allows us to identify pathways near-optimal in terms of mitigation costs according to various perspectives, facilitating a comparative analysis. We have calibrated and analyzed six unique mitigation (or abatement) cost functions, each representing a different paradigm for modeling mitigation costs in aggregated IAMs. Additionally, we analysed different approaches on the optimization paradigm by testing three objective functions to define near-optimal pathways.

We have found that inertia in mitigation costs matters. It is the primary differentiating factor between cost functions, which raises questions about its representation in complex process-based IAMs and resonates with the longstanding debate regarding the inclusion of more dynamic realism in the models [9]. It also appears that using a cost function with inertia generates more near-optimal pathways minimizing intergenerational distribution. Those results call for more research about the impact of explicitly considering inertia in more detailed IAMs and on empirical studies to determine if mitigation cost function are better represented with or without inertia.

In nearby all the physical states of the world, we find generationally and economically robust pathways with rapid emission reduction until 2050 and the deployment of CDR beyond, staying within the range of comparable AR6 scenarios. However, a precise characterization of near-optimal pathways is very difficult as each state of the world yields its own set of pathways, and each CO_2 emissions pathway is associated with an uncorrelated mitigation scenario for non-CO_2 GHGs. Therefore, giving clear guidelines about robust pathways remains beyond the scope of this study, and it encourages further detailed research.

In 4% of the physical states of the World, the intersection is empty, and it is not possible to optimize the intergenerational distribution of mitigation costs while remaining economically robust. Unfortunately, we did not find any significant way to characterize these 'worst case configurations'.

The choice of the objective function used to define near-optimal pathways also matters. Most of near-optimal pathways are similar for all cost functions when NPV is used. The number of common pathways diminishes with max and is very low if NPV_{Diff} is used as objective function.

Considering costs and climate uncertainty in projected mitigation scenarios remains a key objective to define robust scenarios. Here we propose to study this robustness statically but integrating dynamic and recursive approaches to model learning [43] is most probably the next step to push this study further.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.6084/m9.figshare.24411640.

Code and data availability

Code and data available upon request.

Acknowledgments

We thank Aurélie Méjean for the insightful discussions and feedback. K T benefited from State assistance managed by the National Research Agency in France under the Programme d'Investissements d'Avenir under the reference ANR-19-MPGA-0008. T G acknowledges support from the European Union's Horizon 2020 research and innovation programme under Grant Agreements #820829 (CONSTRAIN Project) and #101003536 (ESM2025 Project)

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