Balancing Costs and Benefits

Designing effective global climate policy in an uncertain landscape

Kaj-Ivar van der Wijst

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Kaj-Ivar van der Wijst, maart 2024

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Designing effective global climate policy in an uncertain landscape

Kosten en baten balanceren:
Over het ontwerpen van effectief globaal klimaatbeleid in een onzeker landschap

(met een samenvatting in het Nederlands)

Proefschrift

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The new dawn blooms as we free it.
For there is always light,
If only we're brave enough to see it.
If only we're brave enough to be it.

Amanda Gorman
"The Hill We Climb"

Voor mijn kindje Milo, die ter wereld kwam
drie uur nadat dit proefschrift werd ingediend.
In jouw ogen zie ik de hoop
voor een mooiere wereld.

Table of contents

Units and abbreviations

°C	Degree Celsius
BCR	Benefit-Cost Ratio
CBA	Cost-Benefit Analysis
CB-IAMs	Cost-benefit Integrated Assessment Model
CGE	Computable General Equilibrium model
COACCH	CO-designing the Assessment of Climate CHange costs
DICE	Dynamic Integrated Climate-Economy model
FAIR	Framework to Assess International Regimes, part of IMAGE framework
GDP	Gross Domestic Product
GHG	Greenhouse Gas
IAM	Integrated Assessment Model
IMAGE	Integrated Model to Assess the Global Environment
IPCC	Intergovernmental Panel on Climate Change
MAC	Marginal Abatement Cost
MACC	Marginal Abatement Cost Curve
MIMOSA	Mathematical Integrated Model for Optimal and Stylised Assessment
NDC	Nationally Determined Contribution
NPV	Net Present Value
PRTP	Pure Rate of Time Preference
RCP	Representation Concentration Pathway
SPA	Shared Policy Assumption
SSP	Shared Socio-economic Pathway
TCRE	Transient Climate Response to Emissions
TFP	Total Factor Productivity
UNFCCC	United Nations Framework Convention on Climate Change
USD	United States dollar
/yr	Per year
tCO_2	Ton carbon dioxide
$GtCO_2$	Gigaton carbon dioxide

Introduction

1

1.1. Context

Since the start of the Industrial Revolution, humanity has increasingly emitted carbon dioxide (CO_2) and other greenhouse gases into the atmosphere through the combustion of fossil fuels, other industrial activity, and land use change (especially deforestation). The resulting increase in atmospheric greenhouse gas concentrations has led to more heat being trapped in the earth system, known as radiative forcing. As a result, the global mean temperature has increased by 1.1°C on average during the 2011-2020 period compared to pre-industrial levels (IPCC, 2023). This increase in temperature coincides with other changes in climate (such as more extreme weather) leading to a range of wide-spread impacts on society, ecosystems and the economy across the world (IPCC, 2022a). The impacts of climate change can already be observed now. The heatwave in Northern Europe in 2018, wildfires in Australia in 2019-2020, extreme monsoon floodings in South Asia in 2017, the extreme droughts in East Africa in 2017, and many more extreme weather events have been fully or partially attributed to human induced climate change (Funk et al., 2019; Rimi et al., 2019; Van Oldenborgh et al., 2021; Yiou et al., 2020).

Without climate policies, the global mean temperature could increase to over 3.4°C by the end of this century compared to pre-industrial times as a result of further greenhouse gas emissions (Riahi et al., 2022), leading to unprecedented, widespread and devastating impacts of climate change (IPCC, 2022a). The emission of greenhouse gases needs to be reduced drastically to limit these impacts. This can be achieved with a wide variety of options, such as switching to alternative, clean energy sources, improving efficiency and through lifestyle changes. However, these options are often costly and sometimes require substantial societal transformations.

Global climate change policy, including the level of ambition, has been subject to many debates and negotiations, given the difficulty of substantially cutting down emissions. In 1992, the first international binding agreement (the United Nations Framework Convention on Climate Change, UNFCCC) was agreed upon in Rio de Janeiro, Brazil. Its objective was to "*stabilize greenhouse gas concentrations at a level that would prevent dangerous anthropogenic interference with the climate system*" (UNFCCC, 1992). Five years later, in 1997, the first more concrete action under UNFCCC, i.e. the Kyoto Protocol, was adopted, stating that developed countries should reduce their greenhouse gas emissions by 5% by 2008-2012, compared to 1990 levels (UNFCCC, 1997). Subsequent negotiations to strengthen reductions in developed countries and mitigate emissions in developing countries have, however, been very problematic—including the dramatic failure of the Copenhagen climate summit in 2009. Arguably the most successful agreement was signed in 2015 in Paris and adopted by the 196 countries of the UNFCCC. This agreement stated that global mean temperature increase should be limited to well below 2°C, with efforts to keep the temperature below 1.5°C com-

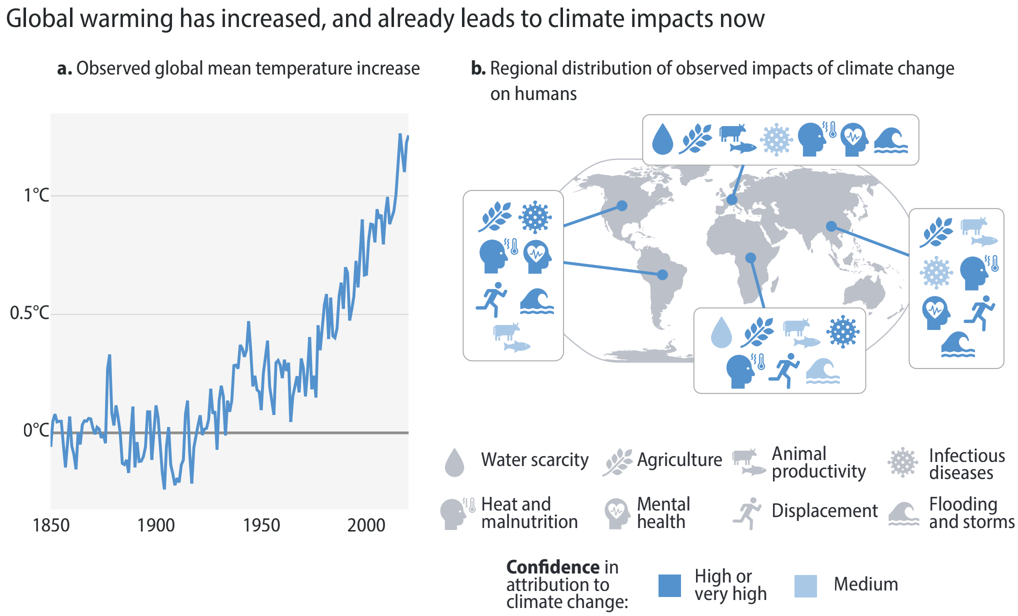

Figure 1.1. *(a) Observed global mean temperature change relative to 1850-1900, as assessed by the IPCC (IPCC, 2023). (b) Observed impacts to human systems that can be attributed to climate change with very high, high or medium confidence, for the regions Europe, Asia, Africa and the Americas (IPCC, 2022a). Missing impacts in a region does not necessarily mean that the impact does not exist, it might also be due to a research gap.*

pared to pre-industrial levels (UNFCCC, 2015). Despite the negotiations, emissions have been rising steadily, from 38 $GtCO_2$-eq/yr in 1990 to 59 $GtCO_2$-eq/yr in 2019 (IPCC, 2022b), mostly because emissions have increased in upcoming economies.

Model-based scenario analysis forms one way to help decision-makers to better understand the climate problem and possible response strategies. One specific form, cost-benefit analysis (CBA), focuses on the economic aspect of climate change by comparing the costs of mitigation to the avoided climate impacts. More ambitious climate policy leads to higher benefits of reduced damages, but also to higher mitigation costs. This leads to many challenging questions: how fast and how deep should emissions be reduced? What are the costs of these policies? What are the expected future climate impacts without action? Where should these emission reductions take place? How much climate impacts will still remain, and how much should regions invest in adaptation against these remaining impacts? To answer such questions, one needs to have insights into the key relationships between emissions, mitigation and climate impacts and the associated uncertainties.

1.2. Scenarios and Integrated Assessment Models

Model-based scenario analysis is often used to explore future pathways with varying assumptions, since the factors that determine the answers to the questions raised in the previous paragraph are strongly interconnected and have deep associated uncertainties. Scenarios are defined as a coherent, internally consistent, and plausible description of possible future states of the world. An important tool to create such scenarios are Integrated Assessment Models (IAMs). These computer models are developed to assess the interactions between the environmental aspects and the human aspects of future climate change and climate policy.

Model-based scenarios do not aim to predict the future but rather sketch out plausible future pathways. Credible predictions are not feasible, as models cannot represent the many social and political forces that can influence the way the world evolves. Instead, by examining different routes, trajectories and developments, scenarios offer a method to map out future landscapes. Scenarios are based on qualitative storylines, a set of derived quantitative assumptions, and final (quantitative) model results. By varying the assumptions and storylines of the scenarios, they shed light on essential sources of system uncertainty.

Box 1.1: socio-economic scenarios and climate scenarios: the SSP-RCP matrix

A set of five Shared Socio-economic Pathways (SSPs) have been created in 2017 to systematically assess different socio-economic developments (Riahi et al., 2017a). These scenarios are based on different assumptions on future evolution of the economy, population, global cooperation and governance, technological growth, and other socio-economic developments and are designed to represent varying levels of challenges in mitigation and adaptation. Each SSP comes with a specific narrative and storyline (Figure 1.2.a):

- *SSP1: Sustainability* – Taking the green road (low challenges to mitigation and adaptation)
- *SSP2: Middle of the road* (medium challenges to mitigation and adaptation)
- *SSP3: Regional rivalry* – A rocky road (high challenges to mitigation and adaptation)
- *SSP4: Inequality* – A road divided (low challenges to mitigation, high challenges to adaptation)
- *SSP5: Fossil-fueled development* – Taking the highway (high challenges to mitigation, low challenges to adaptation)

Each SSP has subsequently been quantified by six major Integrated Assessment Models to create an internally consistent set of quantified scenarios matching each storyline.

The SSPs do not have explicit assumptions on climate policy: in theory, a wide range of mitigation targets can be imposed for each SSP, even though it is much more unlikely that climate policies are adopted in SSP5 than SSP1. For this purpose, the SSPs were combined with the earlier developed Representative Concentration Pathways (RCPs) (Van Vuuren et al., 2011). Resulting from a collaboration between geophysical climate modellers, Earth system modellers and integrated assessment modellers, the RCPs define trajectories of future radiative forcing (until 2100 and beyond). The RCPs cover radiative forcing targets between 2.6 W/m^2 (RCP 2.6) and 8.5 W/m^2 (RCP 8.5). The radiative forcing targets can then be translated into carbon budgets or temperature targets: RCP 2.6 matches a temperature increase of *well below* 2°C, relevant for the Paris Agreement, while RCP 8.5 leads to temperatures of 4°C to 5°C. Later, RCP 1.9 was added to the set of standard RCPs, matching the 1.5°C temperature target of the Paris Agreement.

The SSPs and the RCPs can be combined in a so-called SSP-RCP matrix (Figure 1.2.b). However, not all combinations lead to feasible results: RCP 1.9 is generally assumed to require too strict mitigation action or too much global cooperation that it does not match with the SSP3, SSP4 and SSP5 storylines. Moreover, RCP 8.5 is only compatible with the storyline of SSP5, since it requires levels of emissions that only match the fossil-fuel development storyline of SSP5.

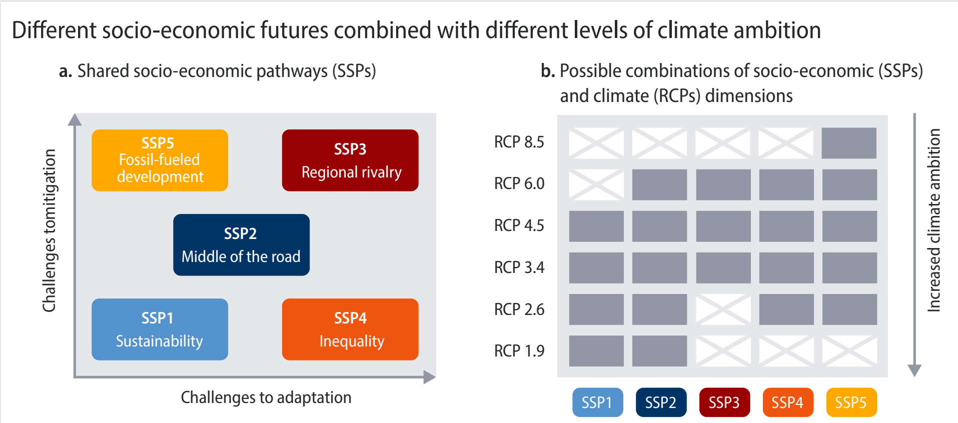

Figure 1.2. *(a) The five different SSPs place on the two axes: challenges to adaptation and challenges to mitigation. (b) SSP-RCP matrix with the feasible combinations highlighted in grey.*

The scenarios in this thesis are created and assessed using IAMs. The goal of IAMs is to help explore the effect of different climate policy options, or the absence thereof, on both the human and environment aspects (Weyant, 2017). The main dynamics of the Earth system, including geophysical processes on land and in the atmosphere, the carbon cycle, ecosystem dynamics, and climate change, are combined with socio-economic drivers like population dynamics, economic activity, technological development, energy demand and production, and agriculture.

IAMs vary in their technological and economic detail, the complexity of the represented geophysical processes, their regional scope in their adopted methodology (e.g. simulation vs optimisation). In general, they can be classified into two main types: detailed-process IAMs and cost-benefit-IAMs (CB-IAMs). Detailed-process IAMs are typically large-scale, complex models with a high level of detail of the socio-economic and technological processes relevant to climate policy, the associated mitigation costs and the representation of feedbacks in the geophysical climate system. These models typically only include some incomplete representation of impacts and damages of climate change (Piontek et al., 2021). Since these models can analyse the impact of a wide variety of climate policies and societal developments on global levels of greenhouse gas emissions and the economy, they are widely used in policy assessments around the world – most notably in the Assessment Reports of the IPCC when analysing different mitigation pathways (IPCC, 2022b). The most common detailed-process IAMs are REMIND, MESSAGE, GCAM, WITCH, IMAGE, AIM and COFFEE, but several dozen others exist.

In contrast to detailed-process IAMs, cost-benefit IAMs aim for a wider, more holistic approach: instead of only focusing on mitigation, these models focus on the interactions between climate policy, climate damages and adaptation, mainly from an economic perspective. In view of their focus on overall dynamics, CB-IAMs typically have a less detailed representation of technological processes and a more stylized representation of the climate feedbacks. They rely on relatively aggregated estimates of the cost of climate policy, often calibrated on the detailed-process IAMs. These mitigation costs are then compared with the economic damages of climate change, which are quantified by aggregated damage functions. Such damage functions typically relate global mean temperature with the economic loss from the associated climate impacts, either economy-wide or with a sectoral disaggregation. The main goal of CB-IAMs is to compare the costs of mitigation with the benefits of reducing the climate damages, thereby optimizing the climate policy target from an economic perspective.

1.3. Previous studies of the costs and benefits of climate policy

The first and most extensively researched CB-IAM is DICE (Dynamic Integrated Climate-Economy model), developed by Nordhaus in 1992 (Nordhaus, 1992a). Due to its transparency, accessibility and ease of extension and modification, DICE continues to play a fundamental role in the literature on cost-benefit analysis of climate policy. Since its first introduction, a plethora of updates and variants have been developed, with DICE2016R2 (Nordhaus, 2017) the latest version, and variants like RICE (Nordhaus, 2010a), AD-RICE (De Bruin, 2014), NICE (Dennig et al., 2015), gro-DICE (Moore & Diaz, 2015), and DSICE (Cai et al., 2012). Other often-used CB-IAMs are PAGE (Hope, 2013), first developed in 1995, and FUND (Anthoff & Tol, 2014), initially developed in 1997.

A key application of CB-IAMs is the calculation of *cost-optimal global temperature targets* or, at the very least, to understand what factors and uncertainties play a role in choosing optimal temperature targets. The optimal target can be calculated by equalizing the marginal mitigation costs to the marginal damages: in other words, by finding the point at which a small additional amount of mitigation starts to cost more than the extra benefits of reduced climate impacts (accounting possibly for adaptation). This analysis is highly dependent on estimates of mitigation costs, and of climate damages. Especially the latter is notably difficult to estimate (see Box 2). Partly for this reason, there has been strong variation in published cost-optimal temperature targets: from 3.1°C using the original DICE version in 1992, 3.0°C with RICE-2010 (Nordhaus, 2010a), 3.5°C with the latest default version of DICE2016R2, all the way to 1.4°C when using different assumptions on discounting and the climate module (Hänsel et al., 2020). In general, the cost-optimal temperature target according to the literature has become gradually lower over time, mainly due to improved insights on the damages of climate change (Kikstra & Waidelich, 2023).

A second application of models like DICE, PAGE and FUND is calculating the *Social Cost of Carbon (SCC)*: the cost of extra climate impacts caused when emitting one additional unit of carbon dioxide into the atmosphere. For the SCC estimates, the damage estimates are critically important. Together with the trend that optimal temperatures have generally decreased over time, the SCC estimates have generally increased over time, but with large uncertainty ranges (Tol, 2005, 2023). As the SCC translates a complex topic (all future additional damages from climate change) into a single, easy-to-interpret, number, it has been used extensively in climate policies around the world. Most notably, the United States have since 2010 based their climate policy on the social cost of carbon. The SCC has even been called the "*most important figure you've never heard of*" by Michael Greenstone, the chief economist of the Council of Economic Advisors under the first Obama administration. However, the concept has also been criticized, because of its high uncertainty and strong sensitivity to assumptions of discounting and time preference, future climate impacts and how to monetize them, and future emission pathways (Pezzey, 2019; Stern, Stiglitz, Stiglitz, 2021; van den Bergh & Botzen, 2015). Moreover, since many impacts of climate change cannot be easily translated into monetary terms, like biodiversity loss, the social cost of carbon can give an incomplete view of the true damages of a unit of CO_2 emissions.

Since impacts of climate change occur on long timescales (end of century and beyond), the way future impacts are compared with present mitigation costs is highly relevant for policy making (Arrow et al., 2013). For this reason, the role of *discounting and intergenerational equity* in the context of CBA has been extensively studied. In literature, discounting future costs is applied to account for (a) future increases in income and GDP, (b) uncertainty of the future and (c) the fact that most people inherently put more weight on present than on future costs. The magnitude of the discount rate has been subject to many debates (Caney, 2014; Creedy &

Guest, 2008; Dasgupta, 2008; Drupp et al., 2018; Portney & Weyant, 2013; Traeger, 2014): while the DICE model typically uses relatively high discount factors (Nordhaus, 2017), Stern (2007) defended a much lower discount rate (or, more precisely, a pure rate of time preference) of almost zero, arguing that it is not ethically defendable to value costs for future generations less than for the present one. Using IAMs, studies have analysed the role of discounting on a range of issues including the optimal temperature (Hof, van Vuuren, et al., 2010), the social cost of carbon (Guo et al., 2006), low-probability high-impact events (Dietz, 2011; Hof, van Vuuren, et al., 2010), and the amount of negative emissions (Emmerling et al., 2019).

While the choice of discount rate already strongly determines the outcome of cost-benefit analyses, the role of other inherently *uncertain processes* are also significant. The most important aspect is the uncertainty surrounding the estimation of climate damages (see Box 1.2 for an overview). Going beyond the traditional climate impacts included in CB-IAMs, including the uncertainty with respect to climate tipping points substantially increases the social cost of carbon (Lontzek et al., 2015b). Moreover, to address decision making under deep uncertainties, strategies have been proposed that go beyond pure cost-benefit analysis and optimal temperature targets: from hedging strategies (Manne & Richels, 1995; Ybema & Bos, 1998) to mini-max approaches (Hof, van Vuuren, et al., 2010; Van Den Bergh, 2004). The Dismal Theory by Weitzman even argues that uncertainty can be so large that meaningful economic cost-benefit analyses become practically infeasible (Weitzman, 2009), although this topic has been subject to further debates (Horowitz & Lange, 2014).

Box 1.2: Estimating the impact of climate change

Estimating the impact and consequences of climate change is complex. Throughout this thesis, we distinguish three levels of climate change impacts: (a) geophysical changes to the climate, (b) physical sectoral impacts, and (c) economic impacts. Each level is assessed using different types of models.

First, the increase of greenhouse gases causes changes in geophysical conditions of the Earth: atmospheric temperatures rise, precipitation patterns change, sea-levels rise, extreme weather events become more extreme and frequent. Highly detailed and computationally expensive climate models have been used to assess these changes, mainly using Global Circulation Models (GCMs) and Earth System Models (ESMs) (IPCC, 2021).

Second, the geophysical changes projected by the GCMs and the ESMs are used as input to sectoral physical impact models. These models are designed to estimate how climate change affects sectors like agriculture, coastal systems, fisheries, forests, energy, diseases, health and more. Many of these impact models collaborate through the ongoing Inter-Sectoral Impact Model Intercomparison Project, ISIMIP (Warszawski et al., 2014).

Third, the economic impacts of climate change can also be estimated (Tol, 2018). While there is a rich literature on mitigation costs, the economic estimation of climate damages remains especially difficult. In current literature, the economic impacts of climate change are typically modelled by either a bottom-up or a top-down approach. The bottom-up approach considers the outcomes of physical impact models described above and/or expert judgement to quantify and aggregate the economic damages into a reduced-form damage function. However, these damage estimates are often incomplete, as they cannot cover all sectors where climate change might have an economic impact. Moreover, some impacts, such as on human health, biodiversity or ecosystems, called non-market damages, are by nature notoriously difficult to monetise (Tol, 2009). Bottom-up estimates therefore typically result in an underestimation of the economic damages of climate change. The top-down approach, on the other hand, combines observed historical fluctuations in weather and (regional) economic output, to obtain empirical, data-driven damage estimates (Burke et al., 2015; Diaz & Moore, 2017; Hsiang et al., 2017; Kahn, Mohaddes, Ng, et al., 2019; Kalkuhl & Wenz, 2020; Moore & Diaz, 2015). While this approach is based on observed data, the associated uncertainty is still large as it is questionable if these relations hold far into the future (Letta & Tol, 2019; Tol, 2019).

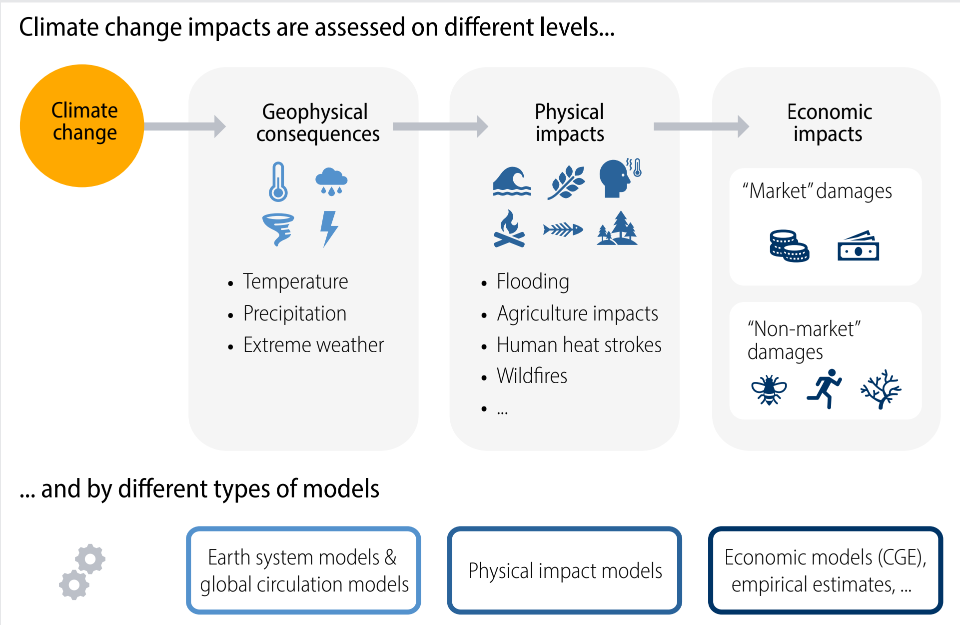

Figure 1.3. *Three levels of climate impacts considered in the literature, with the associated model type used to assess the impacts. In this thesis, we focus on the economic impacts of climate change.*

Another source of uncertainty in determining cost-optimal climate policy trajectories is the inclusion of adaptation. While mitigation efforts reduce emissions, and thereby prevent further climate change, adaptation action gives countries the ability to cope with the damages caused by climate change. Given the challenges to estimate the costs, effectiveness and limitations of adaptation, comprehensive studies covering adaptation for use in IAMs have been sparse. The most prominent studies have extended the DICE, RICE and WITCH models to also include adaptation explicitly, becoming AD-DICE, AD-RICE and AD-WITCH (Agrawala et al., 2011; Bosello et al., 2010, 2014; De Bruin, 2014; De Bruin, Dellink, Tol, 2009; Hof, den Elzen, et al., 2010). Modelling adaptation against sea-level rise has been studied more frequently in IAMs, since the costs and effectiveness of dikes and other infrastructure is better quantifiable than other adaptation measures (Lincke & Hinkel, 2018; Schinko, Drouet, Vrontisi, Hof, Hinkel, Mochizuki, Bosetti, Fragkiadakis, van Vuuren, et al., 2020).

While most of the research with CB-IAMs has focused on target setting and calculation of costs and emission pathways, distributional impacts of climate policy and damages, both between and within countries, have also been addressed in literature. First, effort-sharing regimes have been designed to redistribute mitigation efforts among countries, following pre-defined principles of equity (capacity, equality, responsibility, continuity and cost-efficiency) regimes (Botzen et al., 2008; Höhne et al., 2014; Holz et al., 2018; Leimbach & Giannousakis, 2019; Robiou Du Pont et al., 2017; van den Berg et al., 2020). This literature has mainly looked at target setting (at the national and regional scale). Second, in the context of CB-IAMs, studies have focused on inequality aversion and investigating how costs between regions should be compared in a welfare-utility framework (Anthoff & Tol, 2010a, 2014; Berger & Emmerling, 2020; Gazzotti et al., 2021; Tol, 2012; Tol et al., 2004; van Ruijven et al., 2015). Third, an emerging field of research goes beyond interregional equity and analyses within-region inequality between income groups using a modified version of DICE, called NICE (Dennig, 2018; Dennig et al., 2015).

1.4. Limitations of current research

Despite the extensive body of literature on costs and benefits of climate policy, several substantial limitations can be noted.

First, limited attention is given to comprehensive uncertainty analyses. Several studies have analysed the effect of various assumptions and uncertainties (for instance, related to the discount rate, climate sensitivity or the damages of climate change) on the optimal pathway. However, such studies are often limited in scope (Hänsel et al., 2020; Ueckerdt et al., 2019), only perform a sensitivity analysis (Glanemann et al., 2020; Hope, 2006), or perform a simulation instead of an optimization (Drouet et al., 2015; Lamontagne et al., 2019).

Second, no studies exist that have compared cost-minimising pathways with cost-benefit pathways using the same model framework—except for Nordhaus (2008), who did this for a few selected assumptions regarding discounting and climate targets. Since most CBA studies only focus on cost-optimal pathways, the effect of damages on cost-effective pathways is largely overlooked, including the effect on negative emissions.

Third, both the data on mitigation costs and the data on climate impacts used by the main CBA-studies do not always reflect the latest scientific insights, which can lead to outdated results (Drouet et al., 2015; Hof et al., 2008; Pindyck, 2013a; Pycroft et al., 2011). This constitutes one of the main criticisms of CBA for climate change (Keen, 2020; Mercure et al., 2021; Pindyck, 2013b, 2013a; Sinden, 2019; Spash, 2007; Stern, Stiglitz, Taylor, 2021). When using outdated climate damage estimates, major benefits of mitigation are consequently excluded, which lead to less policy action in situations where the policy is based on cost-benefit analysis, like the US climate policy (Sinden, 2019).

Fourth, most current studies focus on economically optimal outcomes, which does not always lead to equitable outcomes. Most of the scenarios currently submitted to the new IPCC AR6 scenario database (Byers et al., 2022) are based on IAMs operating under a cost-minimisation approach. This means that there is no explicit consideration of equity. The issue of a fair allocation in climate mitigation, however, has been studied extensively in the literature, mainly by assessment of different effort-sharing regimes. Most of the literature that does this, however, only takes mitigation costs into account (Bertsimas et al., 2012; Du Pont et al., 2016; Höhne et al., 2014; Leimbach & Giannousakis, 2019; Pan et al., 2023; Robiou Du Pont et al., 2017; van den Berg et al., 2020). This means that it ignores that countries can also be significantly impacted by climate damages—which also leads to fairness considerations. While there are some exceptions (De Cian et al., 2016; Hof, den Elzen, et al., 2010), these studies use outdated estimates of climate damages.

1.5. Research questions and structure of this thesis

As discussions and choices related to climate policies become increasingly important within society, there is a growing demand for science-based insights into the intricate interplays between mitigation policies and the effects of climate change. This research aims to address some critical policy questions and respond to the knowledge gap identified in the previous section by examining various aspects of cost-optimal climate policy. To that end, the main research question of this thesis is: **"How could climate policy be effectively designed on the basis of cost-benefit analysis, taking into account new insights in the costs of climate policy, the damages of climate change, and key uncertainties?"**

Given the broad scope of this topic, the main research question is divided into four sub-research questions:

1. What are the most relevant sources of uncertainty in cost-benefit analysis of climate change?
2. To what extent do new insights in climate damages alter the outcome of cost-benefit analysis, in particular the cost-optimal temperature target?
3. How do decisions regarding negative emissions and uncertainties in socio-economic development and related adaptive capacities, influence the cost-optimal emission trajectory?
4. How can equity and welfare considerations be combined with cost-optimality in determining regional emission reduction targets?

These research questions will be tackled using five research chapters. The relation between the chapters and the research questions is shown in Table 1.

Chapter 2 provides an analysis of the main sources of uncertainty that have been identified in the literature as critical for the outcomes of cost-benefit analysis. These are damage costs, mitigation costs, the geophysical climate uncertainty, socio-economic developments and discounting (appreciation of future costs versus present costs). By calculating cost-optimal emission with and without using a carbon budget for all combinations of parameters, the chapter mainly address **research question 1**. The uncertainty in carbon price levels and the uncertainty in temperature target is decomposed into contributions of each of the 5 main sources of uncertainty using a Sobol variance decomposition. Moreover, we analysed the effect of including damages when calculating the optimal emission pathway under a carbon budget.

In **Chapter 3**, new, state-of-the-art regional damage functions are created and presented. These damage functions have an internally consistent uncertainty representation, following from the variation of assumptions in the underlying physical impacts models. With these new

	Chapter 2 Uncertainty	**Chapter 3** New damage estimates	**Chapter 4** Overshoot	**Chapter 5** Adaptation	**Chapter 6** Equity
RQ 1: uncertainty					
RQ 2: new damage estimates					
RQ 3: negative emissions and adaptation					
RQ 4: equity					

Main focus of chapter. Addresses the RQ, but not the main focus.

Table 1.1. *Overview of the research questions and their relation with the research chapters.*

damage estimates, we perform a cost-benefit analysis to determine cost-optimal temperature targets, through a multi-model analysis with three different IAMs of varying complexity (MIMOSA, WITCH and REMIND), thereby addressing **research question 2**. Moreover, the Benefit-Cost Ratio is calculated: how much higher are the benefits of avoided damages than the costs of mitigation?

Chapter 4 analyses the effect of overshooting a temperature target or carbon budget, compared to never exceeding the target. Many detailed process IAMs rely on overshoot to reach a target: mitigation action is then slightly delayed, to be compensated by large-scale net negative emissions towards the end of the century. While this is typically cheaper, the overshoot means that more damages are incurred throughout the century than if the temperature goal had not been exceeded. In this chapter, the additional climate damages of this overshoot are compared to the reduced costs of mitigation, for different assumptions of the level of climate damages and discounting. This informs the debate about the (dis)advantages of net negative emissions and therefore addresses **research question 3**. Moreover, in this chapter, the effect of (partial) irreversibility of climate impacts on the cost-optimal amount of overshoot is quantified.

Chapter 5 explores in more detail the implications of different socio-economic pathways (SSPs) on both the mitigation costs and climate impacts. More concretely, we create an SSP-RCP matrix with damage costs, and compares that to the matrix for mitigation costs. A fundamental aspect of the SSPs are the challenges to adaptation. While there is only very sparse literature on adaptation in IAMs, this chapter aims to incorporate adaptation explicitly into CB-IAMs, while taking into account socio-economic limitations to adaptation. These limitations are time-, region- and SSP-specific. Due to its focus on adaptation, this chapter mainly addresses **research question 3**. It also addresses **research question 2** as it uses the newly developed damage cost functions. Moreover, this chapter discusses which aspects influence the mitigation and damage costs, and how they depend on future socio-economic development, which addresses **research question 1**.

As the discussion about climate policy shifts from target setting towards implementation, the question of how the mitigation effort should be distributed across regions in a just and equitable manner becomes increasingly relevant. One of the main points of criticisms of IAMs is the lack of explicit representation of equity. In **Chapter 6**, several ways of incorporating equity are examined by comparing the traditional cost-minimization approach with effort sharing regimes and different welfare representations that take into account regional differences in income, mitigation capacity and damage costs. Specifically, for each of the equity representations, the 2035 regional reduction targets are calculated that are required to reach a 1.5°C temperature target, as well as long-term implications for mitigation costs and inequality. This addresses **research question 4**.

1.6. MIMOSA

The MIMOSA model was developed as part of this research and used in each research chapter of this thesis. MIMOSA, Mathematical Integrated Model for Optimal and Stylised Assessment, is a cost-benefit IAM based on FAIR (Hof et al., 2008) and DICE (Nordhaus, 2017). A schematic overview of the model is shown in Figure 1. It consists of four main modules: economics, emissions, damages, and mitigation.

Economics

The economic module consists of a Cobb-Douglas production function which calculates GDP using exogenous population and total factor productivity. The GDP is divided between a fixed share to investments (determined by a fixed savings rate) and the remaining share to consumption. The investments are added to the global capital stock, which forms together with labour the two production factors for GDP in the next time step. The development of labour is set equal to population developments. MIMOSA is mostly used to maximise discounted utility, where utility is an increasing concave function of consumption.

Greenhouse gas emissions and climate change

CO_2 emissions are calculated based on GDP and an emission factor representing the carbon intensity of the economy, calibrated on the SSPs. Climate change is subsequently modelled on the basis of cumulative CO_2 emissions that are related to global mean temperature (GMT)

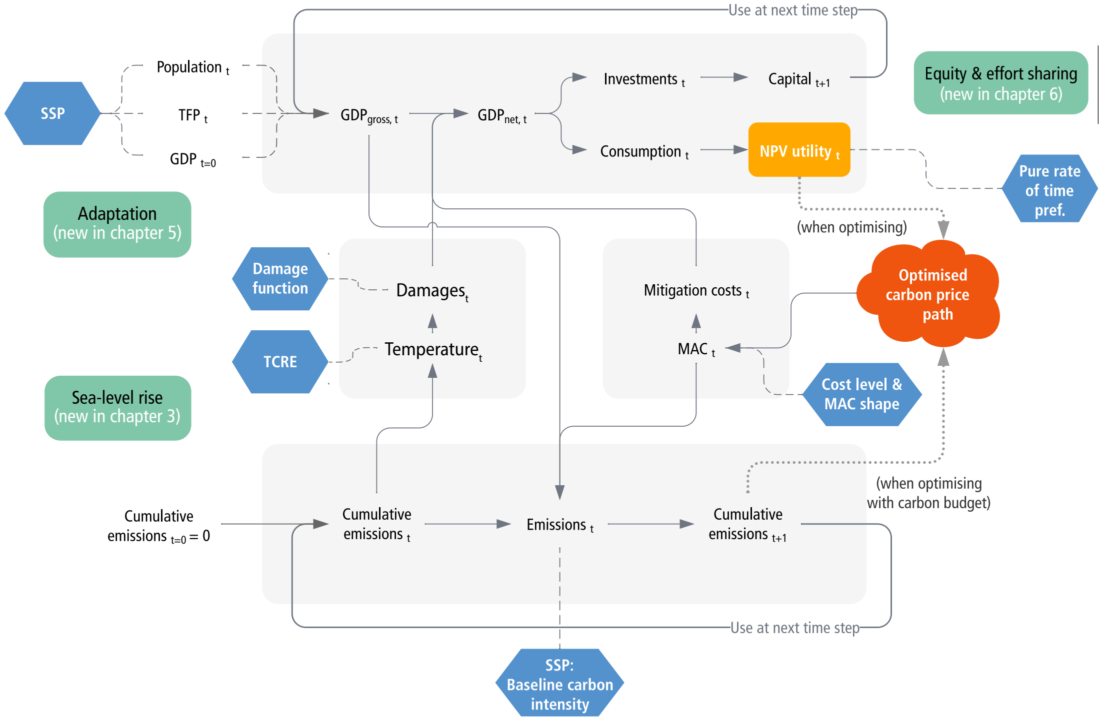

Figure 1.4. *Schematic overview of the MIMOSA model. The blue hexagons represent the main input parameters and sources of uncertainty. The green rectangles are new components that have been gradually added to MIMOSA after the initial version of chapter 2.*

through the linear and instantaneous TCRE (Transient Climate Response to Emissions) relation. This simple climate model is shown to provide more realistic outcomes than the DICE native (and more complex) climate module (Dietz & Venmans, 2019). The TCRE includes the effect of non-CO_2 emissions, which are therefore implicitly coupled to the CO2 emissions. As suggested in previous research (Van Vuuren et al., 2020), the non-CO_2 emissions are correlated with CO_2 emissions, making this a reasonable assumption. There are two linkages between the climate module and the economic module, i.e. via damages and via mitigation.

Damages

The increase in GMT causes GDP loss, quantified through damage functions. In the literature, various estimates of economic damages as function of changes in global mean temperature can be found. In Chapter 2 and 4, three global damage functions are used, covering the current literature range: the DICE damage function (Nordhaus, 2017), a medium damage function resulting from a meta-analysis by Howard & Sterner (2017) and the empirical damage function from Burke et al. (2015). In Chapter 3, 5 and 6, the damage functions are updated by new, state-of-the-art probabilistic regional damage functions developed in Chapter 3. The damages are subtracted from the produced GDP in the economic module.

	Chapter 2 Uncertainty	Chapter 3 New damage estimates	Chapter 4 Overshoot	Chapter 5 Adaptation	Chapter 6 Equity
Regional scope of MIMOSA	Global	Regional	Global	Regional, aggregated to global	Regional
Mitigation cost calibration	AR5	AR6	AR5	AR6	AR6
Damage functions	DICE, Howard et al. & Burke et al.	COACCH (2023)	DICE, Howard et al. & Burke et al.	COACCH (2023)	COACCH (2023)
Optimisation method	Bellman equation	Pyomo/IPOPT	Pyomo/IPOPT	Pyomo/IPOPT	Pyomo/IPOPT
Extensions compared to first version	N.a.	Sea-level rise	Partially irreversible damages	Sea-level rise, adaptation	Sea-level rise, equity

Table 1.2. *Overview of different MIMOSA versions used for each chapter. Note that in chapter 2 and 4, the model was not yet called MIMOSA*.

Mitigation

Mitigation is introduced in the model to reduce emissions. This is simulated via a carbon price. Using time- and scenario-dependent Marginal Abatement Cost (MAC) curves (indicating emission reduction versus the carbon price), the carbon intensity is reduced leading to lower emissions. The MAC curve is also used to determine the mitigation costs, which are deducted from the GDP, similar to DICE and FAIR. The mitigation costs are directly calibrated on the full cost range of the scenarios in the IPCC AR5 Working Group 3 database (chapters 2 and 4 of this thesis) and AR6 database (chapters 3, 5 and 6). The limited availability of negative emissions is modelled by imposing a global and regional minimum emission level. Inertia is modelled by applying a constraint on the difference in CO_2 emissions between two consecutive years.

Regional scale

Chapters 2 and 4 use a global version of MIMOSA. The other chapters use a regionalised version with 26 regions covering the world. The region definition is the same as for FAIR and TIMER of the IMAGE framework (Hof et al., 2011; Stehfest et al., 2014; Van Vuuren et al., 2021).

Regional population, initial capital stock and baseline GDP and CO_2 emissions are directly calibrated on the SSPs (Van Vuuren et al., 2021), and mitigation costs are defined through a regional MAC curve. Each region uses the same global MAC curve (calibrated on the AR6 WG3 scenario database), with a region-specific scaling factor calibrated using MAC curves from the TIMER model.

Table 1.2 provides an overview of the differences in MIMOSA version between research chapters in this thesis.

Optimisation

In chapter 2, the optimal carbon price is calculated using the Bellman Equation with as state variables the cumulative emissions and the capital stock, as control variable the carbon price at each time period and as objective function the discounted utility. The Bellman Equation provides a global optimum, but is computationally expensive. In subsequent chapters, MIMOSA transitioned to the Python-based, open-source optimisation modelling language Pyomo (Bynum et al., 2021; Hart et al., 2011). The model is then solved using the open-source large-scale non-linear solver IPOPT (Wächter & Biegler, 2006).

Implemented extensions

Besides becoming regional, the MIMOSA model has seen several developments throughout this research (highlighted in green in Figure 1.4). Mainly, a sea-level rise module was added in chapter 3, partially irreversible damages in chapter 4, adaptation and adaptive capacity in chapter 5, and equity and effort sharing in chapter 6.

Open source

The MIMOSA model is fully open source and available at https://github.com/kvanderwijst/MIMOSA. Moreover, the model can be easily installed in Python using:

```
pip install mimosa
```

On the optimality of 2°C targets and a decomposition of uncertainty

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Andries F. Hof
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van der Wijst, K., Hof A., van Vuuren, D. On the optimality of 2°C targets and a decomposition of uncertainty. *Nature Communications* **12** 2575 (2021)

Determining international climate mitigation response strategies is a complex task. Integrated Assessment Models support this process by analysing the interplay of the most relevant factors, including socio-economic developments, climate system uncertainty, damage estimates, mitigation costs and discount rates. Here, we develop a meta-model that disentangles the uncertainties of these factors using full literature ranges. This model allows comparing insights of the cost-minimising and cost-benefit modelling communities. Typically, mitigation scenarios focus on minimum-cost pathways achieving the Paris Agreement without accounting for damages; our analysis shows doing so could double the initial carbon price. In full cost-benefit setting, we show that the optimal temperature target does not exceed 2.5°C when considering medium damages and low discount rates, even with high mitigation costs. With low mitigation costs, optimal temperature change drops to 1.5°C or less. The most important factor determining the optimal temperature is the damage function, accounting for 50% of the uncertainty.

2.1. Introduction

As part of the United Nations Framework Convention on Climate Change (UNFCCC), countries have agreed to prevent "dangerous anthropogenic" climate change. In the Paris Agreement, this was specified further as the aim to keep the increase of global mean temperature change well below 2°C and pursuing efforts to limit it to 1.5°C. Determining a goal for international climate policy is extremely complex, as it involves many socio-economic, geophysical and even ethical aspects. To explore and understand this complexity, researchers have developed Integrated Assessment Models (IAMs) describing the interplay of several factors relevant to climate change.

A plethora of IAMs has already been developed, with varying degrees of complexity and differing in focus. One category of models focuses on cost-minimising carbon price or emission pathways to achieve a specific climate target (Calvin et al., 2011; Emmerling et al., 2016; Fujimori et al., 2014; Riahi et al., 2011a; Stehfest et al., 2014). A second category consists of models that determine optimal pathways which balance the costs and benefits of climate policy (Anthoff & Tol, 2014; Hope, 2013; Kypreos, 2007; Nordhaus, 2014; Nordhaus, 2010b). In this type of models, the climate target is an outcome rather than determined exogenously. These two types of models have developed relatively independently. However, in both types, a (shadow) carbon price is used as a key indicator of mitigation effort and costs associated with the transition towards a low-carbon future – and the development of carbon prices and emissions forms a key component in both types of models.

Several studies have analysed the effect of various assumptions and uncertainties (for instance, related to the discount rate, climate sensitivity or the damages of climate change) on the optimal pathway. However, such studies are often limited in scope (Hänsel et al., 2020; Ueckerdt et al., 2019), only perform a sensitivity analysis (Glanemann et al., 2020; Hope, 2006), do not capture the latest insights (e.g., outdated damage functions) (Drouet et al., 2015; Hof et al., 2008; Pindyck, 2013a), or perform a simulation instead of an optimisation (Drouet et al., 2015; Lamontagne et al., 2019). Moreover, no studies exist that have compared cost-minimising pathways with cost-benefit pathways using the same model framework - except for Nordhaus (2008), who did this for a few selected assumptions regarding discounting and climate targets. Such a comparison would provide insight into under which conditions taking into account climate damages would change the cost-optimal carbon price and emission pathway, given a fixed climate target.

A comprehensive analysis of cost-benefit versus cost-minimising pathways, including an uncertainty analysis of the most important parameters, requires a model that is simple enough to use mathematical optimal control theory techniques but complex enough to capture the relevant technological and socio-economic dynamics. Moreover, the model should easily be calibrated to the literature ranges. In this paper, we develop a flexible and transparent model to calculate the optimal carbon price path under a set of assumptions regarding damage functions, temperature goals, mitigation costs, climate sensitivities, discount rates and socio-economic developments. With this model, we directly compare the insights of the two main Integrated Assessment Modelling communities: the cost-minimising models which focus on how climate targets (e.g., a carbon budget) can be reached, without taking damages into account, and the cost-benefit models which compare the marginal mitigation costs to marginal damages to calculate optimal temperature goals.

With this model, we first analyse each parameter's effect on the timing of mitigation in cost-minimising paths (also called cost-effective paths). We then quantify how these cost-minimising mitigation paths are impacted if the economic impact of climate damages is included, and not only mitigation costs. We analyse how the relative importance of each parameter's uncertainty varies over time.

Besides cost-minimising paths with a carbon budget, we analyse optimal cost-benefit paths (which do not require a preset carbon budget). In particular, the resulting optimal end-of-century temperature has been the subject of much research. Here, we provide a comprehensive analysis of how this optimal temperature depends on the literature ranges of the relevant parameters—moving beyond current literature which only considers a limited range of damages or mitigation costs (Glanemann et al., 2020)—and investigate under which assumptions the 2°C temperature target set by the Paris Agreement is optimal.

We move beyond studies presenting sensitivity analysis of the assessed parameters and conduct a systematic uncertainty analysis using ranges based on literature. We also analyse the interaction between parameters and assess to which degree uncertainty in individual parameters affect total uncertainty in the optimal carbon price or end-of-century temperature.

The model used in this paper is based on a simple economic growth model (Figure 1). This model shows some similarities with the DICE (Nordhaus, 2014) and the FAIR (Hof et al., 2008) model. The production function is combined with estimates on mitigation costs and climate damages from recent literature. In the model, a global carbon price is applied such that the discounted utility is maximised. This transparent model is still solvable using the Bellman equation, which guarantees mathematical optimal solutions.

The model is calibrated using literature ranges on parameters relevant for global climate policy (highlighted in colour in Figure 1). The socio-economic variables are obtained from the Shared Socio-economic Pathways (SSPs, blue) (Riahi et al., 2017b). The damage functions (green) cover the low range of damage functions (DICE-2016R2 damage function (Nordhaus & Moffat, 2017)), the medium (based on a meta-analysis by Howard et al. (2017) of empirical and traditional IAM estimates and referred to as Howard Total in this article), and the high

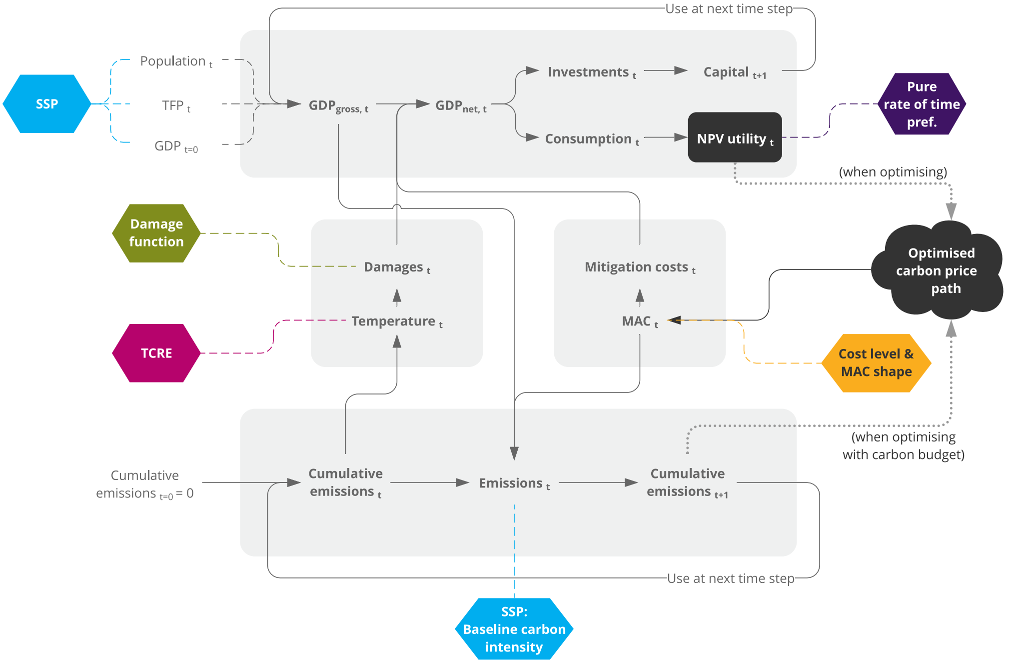

Figure 1. Schematic representation of the model. *The model consists of an economic module (top) with a Cobb-Douglas production function, and an emission module. The interactions between these two modules occur through damages and mitigation costs. The coloured boxes represent the parameters for which we use a representative range from literature. The carbon price path, in black, is the input variable of the model and the control variable in the optimisation.*

range (long-run empirical damage function from Burke, Hsiang and Miguel (2015)). Both the Transient Climate Response to Emissions (TCRE, pink), linking temperature to cumulative CO_2 emissions, and the mitigation costs (yellow), are calibrated to IPCC AR5 data (IPCC, 2013; IPCC, 2014) and both span the 5-95th percentile range (Van Vuuren et al., 2020). Finally, we use three values for the pure rate of time preference (purple): 0.1%, 1.5% and 3% per year. The values used for each parameter are summarised in Table 1. While other parameters like different technological growth assumptions, social inertia and welfare are relevant, their impact on this paper's main policy outcomes is significantly smaller than the five main parameters we focus on in this paper (see Discussion).

With our model, we discuss how these parameters affect optimal carbon price paths and associated emission paths in a cost-minimising setting, by imposing a carbon budget. When considering cost-minimising pathways reaching the Paris Agreement's temperature target, including medium damages can double the initial carbon price compared to purely considering mitigation costs. Moreover, decreasing the pure rate of time preference from 1.5%

Parameter	**SSP**	**Damage function**	**TCRE**	**Mitigation cost level**	**Pure rate of time preference**
Values	SSP1, SSP2*, SSP3, SSP4, SSP5	No damage**, DICE 2016R2 (low), Howard Total (middle)*, Burke (LR) (high)	0.42, 0.62*, 0.82 °C/1000 $GtCO_2$	From IPCC AR5 consumption losses: low, medium*, high	0.1%/yr, 1.5%/yr*, 3.0%/yr

*: default parameter value if not specified

**: only used in cost-minimising scenarios with a fixed carbon budget

Table 1. *Values for the main parameters of the model.*

to 0.1% also doubles the initial carbon price. Over the century, the cost-minimising carbon price mostly rises with per capita GDP growth. The level of mitigation costs dominates the variance of the carbon price. The discount rate, damage function and socio-economic scenario contribute in almost equal part to the remaining variance, with a drop in absolute variance around 2070. Consequently, the choice of discount rate and how climate damages are valued have a substantial effect on the carbon price in a cost-minimising setting. To reduce the uncertainty in climate policy, these choices have to be made as soon as possible.

In a cost-benefit setting (without carbon budget), even with high mitigation costs, the optimal end-of-century temperature with medium damages and a low discount rate does not exceed 2.5°C. For low mitigation costs or with the high damage function, we find an optimal temperature of 1.5°C or less. The effect of a different TCRE is negligible for scenarios with an optimal temperature between 1.5 and 2°C. Over 50% of the uncertainty comes from the damage function, compared to only 2% from the TCRE. Many of these results individually are consistent with previous research. This paper presents a comprehensive overview of the relative importance of each of these results.

2.2. Results

2.2.1. Optimal carbon price paths with a fixed carbon budget

This section focuses on optimal carbon price paths reaching a fixed carbon budget in 2100 (cost-minimising setting). The carbon budget here is 1344 $GtCO_2$, which leads to a 2°C temperature increase compared to pre-industrial with 67% certainty given the normal distribution of the TCRE (see SI. 4.1). The effect of changing various parameters on the shape of the carbon price and, subsequently, the emission path, is shown in Figure 2. Each experiment compares the cost-minimising path without damages (solid lines) with cost-minimising paths including damage costs, based on the medium damage function Howard Total (dotted lines). Moreover, the effect of varying each remaining parameter individually (mitigation cost level, SSP, TCRE and discount rate) is analysed (various colours in each subplot). In each of the experiments, we use the default values of Table 1, unless specified otherwise.

In each of the experiments, the carbon prices increase over time, before they start falling again when the imposed minimum emission level, set to represent restrictions on carbon dioxide removal technologies (see Methods), is reached (if at all). Including damages leads to a shift of the mitigation effort from the end of the century towards the present: the optimisation aims to reduce the impact of damages on GDP development by increasing the mitigation effort early on. Consequently, the carbon price path becomes more linear. This impact depends on the damage function and is smaller for the DICE damage function and strongest for the Burke function. In fact, in the latter case, the optimisation can lead to smaller carbon budgets than the target.

Unsurprisingly, higher marginal abatement costs lead to higher carbon prices to reach the given carbon budget (Figure 2a). In the no-damage scenario, the carbon price path is linearly dependent on the height of the MAC and so there is no impact on timing (Supplementary Figure 6.1). Interestingly, when including damages, the initial carbon price (in 2025 to avoid initial inertia constraints) depends on the interaction between damages and mitigation costs. For high mitigation costs, the medium damage function implies an initial price that is 32% higher than without taking damages into account, while for low mitigation costs, this is 282% higher. When using the higher (Burke) and lower (DICE) damage functions, this effect also exists but is larger or smaller, respectively. When assuming medium damages, taking into account damages to determine the optimal emission pathway only leads to a substantially different optimal emission pathway if low mitigation costs are assumed, with very early reductions and hardly any net negative CO_2 emissions.

The SSP substantially impacts the optimal carbon price (Figure 2b) (see also (Riahi et al., 2017c)). First of all, the difference in baseline emissions (e.g., between SSP1 and SSP5) explains that the SSP5 carbon price path grows earlier and more rapidly. Despite this higher carbon price, the minimum emission level is reached before the end of the century in SSP5. Second, since utility is derived from per capita consumption, a high population growth combined with a low GDP, as in SSP3 (Supplementary Figure 1.2), means that end-of-century costs have a larger impact on total cumulative utility. Therefore, the mitigation effort is more linear in SSP3: a much higher initial carbon price is followed by lower carbon prices towards 2100 compared to the SSP1 and SSP5 paths. In other words, cost-minimising paths without damages lead

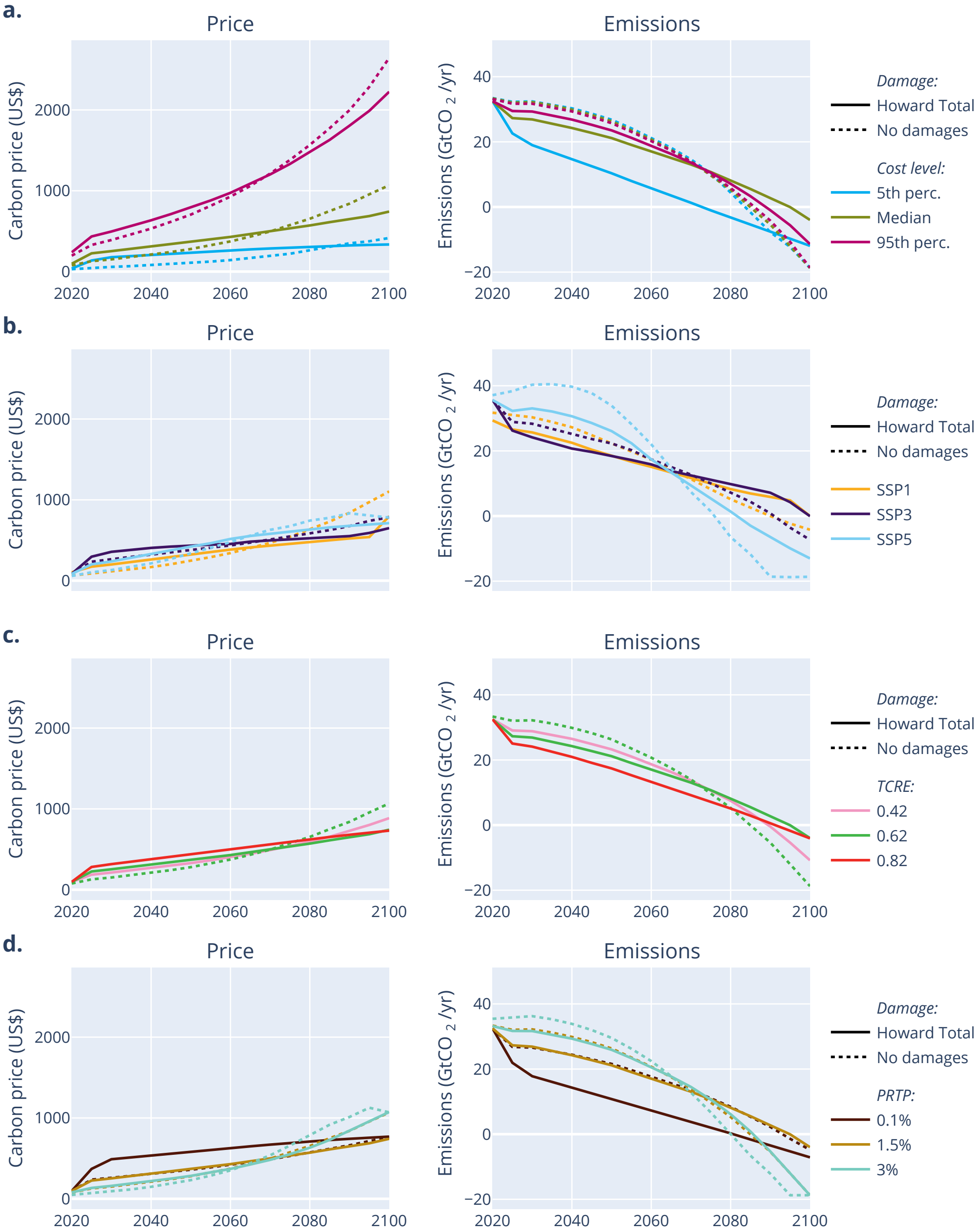

Figure 2. Optimal carbon price paths (left) with corresponding emission path (right) for different scenarios with a 1344 GtCO2 carbon budget (cost-minimising setting). *For each scenario the default parameters (see main text) are used, with one parameter changed (a: mitigation cost level, b: SSP, c: TCRE, d: pure rate of time preference). The solid lines correspond to purely cost-minimisingpaths (no damages), the dotted lines take into account the medium damage function Howard Total.*

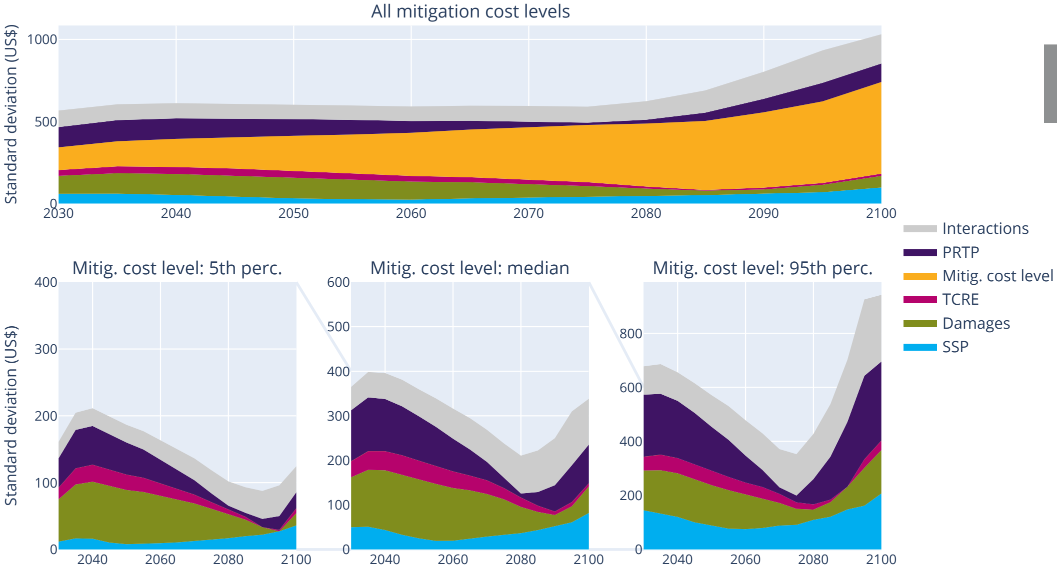

Figure 3. Contribution to the variance of each parameter as a function of time using Sobol Indices (cost-minimising setting). *In the top row, all parameters are considered. In contrast, in the bottom row, the same analysis is performed while fixing the mitigation costs at three distinct levels: low, medium and high costs. Note that for clarity, the square root of the variance – the standard deviation – has been shown: the unit then becomes US$ instead of the square of it. The decomposition with variances is shown in Supplementary Figure 2.2.*

to initially exponentially increasing price paths, unless one assumes that our future society will not be much richer than today, confirming previous findings (Goulder & Mathai, 2000).

The TCRE dependence (Figure 2c) is relatively straightforward: the higher the TCRE, the higher the impact of damages on the carbon price and emission pathway (thus leading to a stronger preference for early mitigation). In fact, the initial carbon price increases almost linearly with the TCRE (Supplementary Figure 6.3).

Higher discount rates shift mitigation efforts towards the future (Figure 2d). In a cost-minimising setting without damages, decreasing the pure rate of time preference from 3% to 1.5% almost doubles the initial carbon price. Moving from 1.5% to 0.1% almost doubles the initial price again.

Subsequently, we analyse the combined effect of all parameters on the optimal carbon price and determine each parameter's contribution to the total variance. This is quantified by Sobol indices, calculated with a Monte Carlo simulation using each combination of parameter values of Table 1 (see Methods): the total variance is split in partial variances attributed to each parameter, along with interactions between them. As we consider scenarios with a fixed carbon budget here, we focus on the determinants for the optimal carbon price only. The top panel of Figure 3 shows the standard deviation of the optimal carbon price and its determinants over time. The standard deviation remains relatively constant until the mid-2060s, after which it increases strongly, as a result of the increasing mean values of all carbon prices over time. The dip in variance in the first decade comes from the constraining effect of inertia to reduce initial emissions. The main contribution to the variance is by far the mitigation cost level, especially in the longer term. However, the initial carbon price, however, is also strongly influenced by future socio-economic developments (through the SSPs, see also Supplementary Figure 2.4). To better analyse the contribution of the remaining parameters, we perform the same analysis but by fixing the cost level at low, medium and high mitigation costs (bottom three panels of Figure 3).

The variance of the optimal carbon price due to other determinants is the highest towards the end of the century. Interestingly, for all cases presented there is very little variance around 2070. This can be explained by the fact that most changes in parameter values induce a

Figure 4. Costs versus benefits (cost-minimising setting). *The costs are calculated as the net present value (NPV) of abatement costs as a share of GDP, while the benefits are the NPV of avoided damages as a share of GDP compared to the baseline SSP scenario, for each scenario reaching the carbon budget of 1344 GtCO2, and for each combination of parameters of Table 1.*

shift in mitigation effort either towards the present or towards the end of the century. They therefore increase (or decrease) the initial carbon price, and decrease (or increase) the final carbon price – leading to similar carbon prices by 2070.

The SSP, discount rate and damage function contribute equally to the total variance for medium mitigation cost levels. For low mitigation costs, the damages become more important. In contrast, the SSP becomes more dominant for high mitigation cost levels, where the marginal mitigation costs become substantially larger than the marginal damages. The contribution of the uncertainty in TCRE is negligible, accounting for less than 0.5% of the variance. This confirms previous findings (Van Vuuren et al., 2020), which state that the socio-economic uncertainty is far more important than the geophysical uncertainty in scenarios with stringent temperature targets.

For all the cost-minimising 2°C pathways, it can be determined whether the monetary benefits (damages avoided compared to a baseline scenario) outweigh the costs (net present value of abatement costs). While this does not imply that the pathways are optimal in a cost-benefit setting, at least the pathways lead to net benefits compared to baseline if this is the case. This comparison is very similar to the comparison of the Stern Review (Stern, 2007), in which a stringent scenario was compared to no mitigation at all. Of all parameter combinations with either medium or high damages, 95% lead to avoided damages exceeding mitigation costs (Figure 4). The remaining 5% consists mostly of high mitigation cost scenarios. For the DICE damage function, only 40% of all parameter combinations lead to higher benefits than costs. The magnitude of the damages, and much less the magnitude of the mitigation costs or the discount rate, therefore largely determines whether the benefits of 2°C outweigh the costs. The optimal balance between avoided losses and mitigation costs – the cost-benefit setting – is another question, however, and is discussed in the next section.

2.2.2. Cost-benefit paths (without a carbon budget)

This section considers purely cost-benefit scenarios, without carbon budget or temperature target: the optimal price path results from an optimal balance between mitigation costs and damages. We discuss the optimal temperature in 2100 for different parameter combinations and subsequently, we analyse the contribution to the variance of the optimal temperature resulting from each parameter. Finally, we briefly discuss the resulting shape of the optimal carbon price path in a cost-benefit setting.

Figure 5 shows the optimal temperature in 2100 for all combinations of the discount rate, damage function, mitigation cost level, and SSP. A 2°C temperature target or lower is found to be optimal in most parameter combinations in cost-benefit setting with high damages or with a low discount rate, the latter with the exception when combined with DICE damages. Low discounting does not always lead to optimal temperatures below 2°C, especially

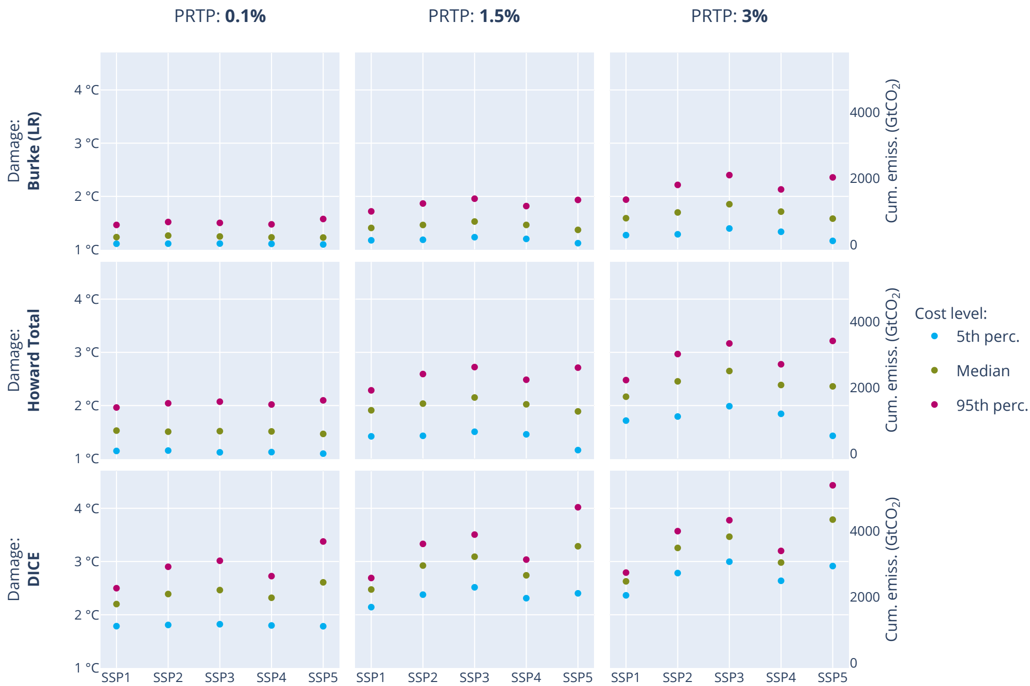

***Figure 5. Optimal temperature in 2100 (cost-benefit setting)**, for three different pure rate of time preference rates (columns), three damage functions (rows) and mitigation cost levels (colors). The median value of the TCRE is used for each scenario here. Therefore, the end-of-century temperature corresponds linearly to the cumulative CO2 emissions from 2020 to 2100.*

if high mitigation costs and medium to low damages are assumed. However, in most cases, the optimal temperature is 3°C or significantly less with low discounting, except for SSP5 socio-economic developments. The optimal temperature in SSP5 is consistently higher than in other SSPs: between 3°C and 4.5°C. On the other hand, SSP1 and SSP4 have consistently lower optimal temperatures (between 1°C and 3°C), directly correlated with the baseline emissions of these SSPs. In fact, with a high discount rate or low damages, the influence of the SSP becomes much more important. This is discussed in more detail below.

The effect of assuming a low or high TCRE instead of the median value is mostly linear with the optimal temperature (Supplementary Figure 3.4): the higher the optimal temperature with median TCRE, the higher the effect. A lower TCRE leads to a lower optimal temperature. Conversely, a high TCRE leads to a higher optimal temperature, but this effect is dampened by an increased abatement effort to counter the increased damages. Scenarios with an optimal temperature around 2°C hardly see any impact of a change in TCRE.

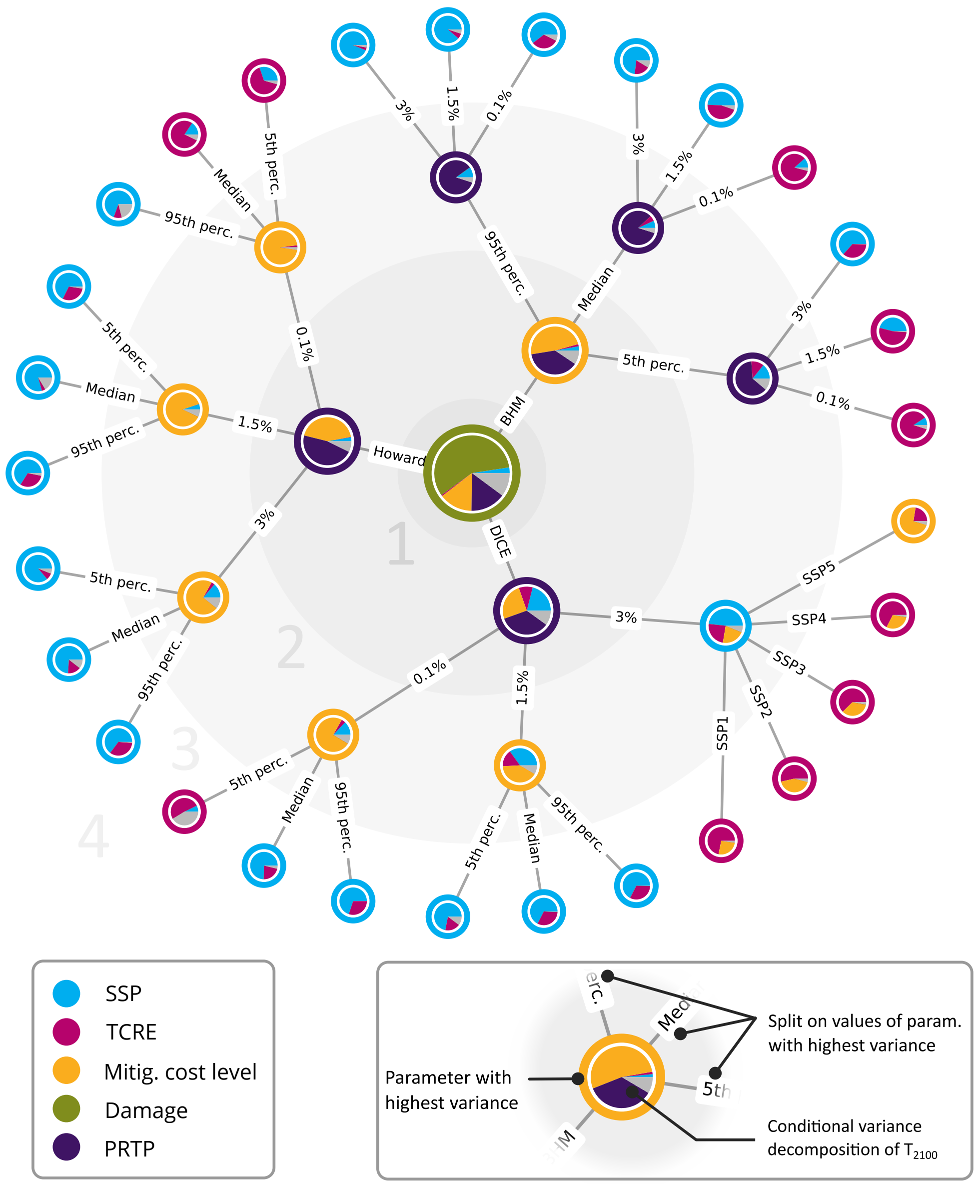

Figure 6. Conditional variance tree for the temperature in 2100 (cost-benefit setting). *At the central node, a Sobol variance decomposition is performed on the whole set of parameter values. The pie chart represents the percentage each parameter contributes to the total variance. The outer colour is the parameter with highest variance. The node is split in each of this parameter value, and the variance decomposition is repeated with this parameter value fixed. By repeating this process, a conditional variance tree is created. The grey colour in each node represents the interaction terms in the Sobol decomposition.*

To assess the contribution to the variance of each model parameter on the optimal temperature, we perform a Sobol variance decomposition using the same method as for the variance decomposition of the carbon price in a cost-minimising setting. The difference here is that we focus on the optimal temperature in 2100 instead of the carbon price over time. The total variance is split into percentages attributed to each parameter. When considering all combinations of parameter values, the damages are responsible for the highest variance (58%), followed by the discount rate (15%) and the mitigation cost level (14%). This is shown as the central node in the conditional variance tree of Figure 6. We split on the variable with the highest variance (damages) and perform the same analysis, conditional on each value of this parameter. By repeating this process, we fix the parameters' values with the highest conditional variance and obtain a tree structure.

Interestingly, the parameters with the highest variance within each level of this tree (large grey circles in Figure 6) are not identical. For instance, with a medium or high damage function (Howard Total and Burke), the discount rate and mitigation cost level dominate the variance since the mitigation effort level is then mainly determined by how much weight is given to costs for future generations. When considering a low damage function (DICE) with a high discount rate, where the optimal emission path is closer to the baseline emissions, the next parameter with the highest variance is the SSP. The mitigation costs in this case only play a significant role in SSP5 (with its higher baseline emissions), whereas, for the other SSPs, the geophysical uncertainty in TCRE dominates the variance.

The interaction terms, represented in grey in Figure 6, can be further decomposed. As shown in Supplementary Fig. 3.8, the two highest interaction terms are between SSP and the damage function (due to the large differences in baseline between SSPs, where some SSPs are much more sensitive to climate damages) and between the TCRE and the damage function (since the TCRE has a direct influence on the temperature and therefore the damages). This shows that while the first-order variances of SSP and TCRE are small, their total variance is larger when including interaction terms.

The timing of mitigation is obviously at least as important as the optimal temperature. The optimal carbon price paths in a purely cost-benefit setting increase almost linearly (Supplementary Figure 3.3), consistent with simpler settings in earlier studies (Goulder & Mathai, 2000). While greater damages lead to slightly steeper carbon price paths, most factors influence mainly the initial carbon price. The exception here is the SSP (panel b, Supp. Fig. 3.3): the SSP determines mostly the steepness of the carbon price path. Similar to cost-minimising paths, the SSP3 path is much flatter than the other SSPs. The uncertainty in carbon prices in the cost-benefit setting (sometimes called the social cost of carbon) can be directly compared to the carbon price's corresponding uncertainty in the cost-minimising setting (cf Fig. 3 and Suppl. Fig 3.4b). Interestingly, uncertainty in mitigation costs has a much smaller impact on the level of the cost-benefit carbon price (Supplementary Figure 3.4 a and b): it explains around 10% of the total variance. The damage function (45%-60%) dominates the variance instead. The discount rate is the most important factor for low damages, while conditional on high damages, the mitigation cost level contributes most to the variance.

2.3. Discussion

This paper focuses on the economic aspects of climate policy by discussing cost-minimising paths and optimal temperatures in a cost-benefit setting. The approach provides insight into the critical factors that determine the attractiveness of various mitigation pathways. Moreover, it allows extending on current literature research on cost-benefit analysis.

This paper also adds some nuance to the claims of recent literature (Glanemann et al., 2020; Hänsel et al., 2020) stating that the 2°C temperature goal, as set in the Paris agreement, is indeed optimal. Glanemann et al. (2020) focus on the Burke baseline damage functions (short run), which correspond roughly to the Howard Total damage: the optimal temperature in 2100 using Burke (short run) divided by the results using Howard Total damages has a mean of 0.97 (standard deviation of 0.07). While the optimal temperature using medium mitigation costs and a small discount rate is indeed very close to 2°C, different mitigation cost levels or discount rates have a strong impact, leading to optimal temperatures between 1.1 and 3.5°C. This confirms the importance of considering the full literature range for these parameters. On the other hand, Glanemann et al. observe a larger impact of using different climate sensitivities (moving the optimal temperature from 2°C to 1.5 or 2.5°C for different climate sensitivities). This difference is likely due to DICE's different climate module: while we use the instantaneous TCRE relation, DICE uses a two-box model with much longer lag times. Similarly, our results are in line with Hänsel et al. (2020), considering that they used a similar range in social discounting parameters, but only our medium estimates for climate damage and mitigation costs. Our full range of optimal climate targets is much larger. Whereas Drouet et al. (2015) use emission pathways generated using more detailed IAMs, the damages were only added afterwards. Considering the climate damages in the optimisation leads to significant differences in carbon prices, as shown in Fig. 2. Moreover, the optimal carbon budget candidates selected in Drouet et al. (2015) are higher than our optimal carbon budgets, mainly due to the much lower, now outdated, damage functions employed in their paper. Finally, our uncertainty decomposition contrasts with Lamontagne et al (2019), as we show a much larger uncertainty from damage function and mitigation costs. This difference is directly attributable to the use of full literature ranges instead of much smaller damage and abatement cost sensitivity ranges in ref (Lamontagne et al., 2019).

Sensitivity runs. Moving from a quadratic MAC to a cubic MAC has a small effect on the optimal temperatures (Suppl. Figure 5.2): more cheap mitigation options are available with a cubic MAC, but options become quickly expensive after these cheap options have been implemented. This leads to a smaller spread in optimal temperatures. In the cost-benefit setting, using a cubic MAC only significantly effects the carbon price in the low mitigation cost scenario (Supplementary Figure 5.3), where the carbon price is increased by about 20%, necessary to reach the more expensive high mitigation options of the cubic MAC. On the other hand, the cubic MAC only has a significant effect on the carbon prices in a cost-minimising setting when assuming high mitigation costs: to reach the 2°C target, very high carbon prices are warranted with high mitigation costs, where the difference between the MACs is highest (Supplementary Figure 5.1).

As an alternative welfare formulation, we have performed the same analysis with the PRTP and elasticity of marginal utility (elasmu) values from a recent expert elicitation (Drupp et al., 2018). Using 172 combinations of these parameter values, the 5th, 50th and 95th percentile values can be calculated (see SI.7), giving a significantly wider range in the social discount rate. In fact, instead of using the PRTP values of 0.1%, 1.5% and 3% with a fixed elasmu of 1.001, the Drupp et al. (2018) survey yields 0% and 0.5, 0% and 1.5 and 2% and 2.5 for the PRTP and elasmu values respectively. However, since these values cannot be considered to be uniformly distributed (as in our main analysis), the effect on the uncertainty is very small (Supplementary Figure 7.3 and 7.6). For the main analysis, we have chosen to use the literature range of PRTP values instead of focusing on a single expert elicitation.

Changing the minimum emission level from -20GtCO_2 to 0 (therefore avoiding an emission/temperature overshoot) influences the results in varying ways (SI 5.2). In the carbon budget setting, the mitigation effort is shifted towards the first half of the century due to the extra constraint. With medium assumptions and no damages, this leads to an 18% higher carbon price. Assuming greater damages reduces this difference since these scenarios already used less net negative emissions. In the cost-benefit setting, the impact of avoiding overshoot is negligible for scenarios ending up above 2°C, since the optimal emission paths leading to these temperatures hardly use net negative emissions in the first place. For lower optimal temperatures, the constraint leads to an increase in end-of-century temperature up to 0.2°C in SSP2 and up to 0.3°C in SSP5.

Many factors are not captured in the current model and therefore insights in general outcomes are more interesting than the absolute numbers. Key factors not included are, for instance, heterogenous impacts (for different societal groups) and the possibility of environmental feedbacks and tipping points, possibly with stochastic behaviour. we have chosen the Howard Total damage function to account for the missing tipping point modelling, which includes catastrophic damages through a proxy for tipping points in a traditional IAM damage function. Other factors like inequality and regional heterogeneity cannot be addressed with our global model – moving to a regional model would provide further insights.

In this research, we have considered a large range of damage functions, implicitly considering a wide array of assumptions on climate impacts. In future work, it would be interesting to disentangle this uncertainty. For example, recent work has shown that the role of biodiversity and ecosystem services and the associated scarcity of environmental goods is relevant for cost-benefit work (Bastien-Olvera & Moore, 2020). Including natural capital in the production function would be a first step towards decomposing the damage uncertainty. Using bottom-up sectoral climate damages could decompose this further.

Parameter validity. The Burke damage function (Supplementary Figure 1.4) as calculated using our calibration reports end-of-century damages which are significantly lower than the damage function shown in Burke et al. (Extended Data Figure 6) (Burke et al., 2015). This difference is due to a combination of three factors: 1) damages to the GDP also affect future GDP growth due to a loss in capital, 2) Burke et al. assume a linear increase in temperature instead of the baseline SSP temperature increase and 3) the global estimates are slightly lower than the sum of local estimates due to downscaling factors and the non-linearity of the temperature-growth impact relationship.

Uncertainty. Throughout this paper, we have considered the extensive range of key parameter values as the source of uncertainty. However, these represent the fact that these parameter's precise values are unknown – and not the uncertainty in a stochastic sense. Adding stochasticity to the model would allow for a more comprehensive investigation of the impact of tipping points. Previous work on stochastic IAMs (Helwegen et al., 2019; Lontzek et al., 2015a) could be extended to include the literature ranges of the parameters provided in this paper, and possibly be extended with data on socio-economic tipping points (Van Ginkel et al., 2020). This would effectively widen the range of possible damages.

Suitability of the model. The use of IAMs, in general, has been criticised both for cost-benefit analysis (for models like DICE) (Pindyck, 2013a) and cost-minimising analysis, but this general critique has been discussed elsewhere. Our analysis' added value is that it allows us to investigate the effect of critical, normative assumptions on policy-relevant quantities, like the magnitude of the carbon price or the optimal temperature. The simple model allows for more transparency in how our results are obtained and our parameters are calibrated. Moreover, some of the criticisms, such as ad hoc input parameters and damages (Pindyck, 2013a), are addressed using the full literature ranges of key parameters.

Given the extensive range of optimal temperatures, one can ask how to use the results. It should be noted, however, that dealing with uncertainty and normative choices is part of climate policy decision-making, with or without insights of different models. This will include deciding on acceptable risk levels and normative choices like the discount rate. From our analysis, the risk of high damages appears to be higher than the risk of high mitigation costs. If this is combined with the suggestion of Stern and, more recently, Emmerling et al. (2019)

(Emmerling et al., 2019) that low discount rates are warranted for long term climate policy, our results confirm that for low discount rates and medium to high damages, cost-optimal temperatures are in line with the long-term objectives of the Paris Agreement. Moreover, research could possibly reduce some of the uncertainties over time.

2.4. Methods

2.4.1. The model

A schematic overview of the model is shown in Figure 1. The economic module (top grey box) consists of a Cobb-Douglas production function which calculates GDP using exogenous population and total factor productivity (Riahi et al., 2017c). The GDP is divided between a fixed share to investments and the remaining share to consumption. The investments are added to the global capital stock, which forms together with labour the two production factors for GDP in the next time step. The development of labour is set equal to population developments. The goal is to maximise discounted utility, where utility is an increasing function of consumption.

The next component of the model is the emissions module. CO_2 emissions are calculated based on GDP and an emission factor representing the carbon intensity of the energy system (bottom grey box in Figure 1). The interactions between the emission module and the economic module occur through two mechanisms: damages from climate change, and mitigation costs. Unlike the DICE model, which uses a two-box climate module (which has recently been shown not to be able to reach a 2°C target (Howard & Sylvan, 2020)), the cumulative CO_2 emissions in our model are translated into global mean temperature (GMT) through the linear and instantaneous TCRE (Transient Climate Response to Emissions) relation. This simple climate model is shown to provide more realistic outcomes than the DICE climate module (Dietz & Venmans, 2019). The TCRE includes the effect of non-CO_2 emissions, which are therefore implicitly coupled to the CO_2 emissions. As suggested in previous research (Van Vuuren et al., 2020), the non-CO_2 emissions are correlated with CO_2 emissions, making this a reasonable assumption.

The increase in GMT causes GDP loss, quantified through damage functions. To counter these damages, a global carbon price is used at every time period, which causes a reduction of emissions as defined through a quadratic Marginal Abatement Cost (MAC) curve with technological learning (learning-by-doing). The MAC also quantifies the mitigation costs, which are deducted from the GDP, similarly to DICE and FAIR (Hof et al., 2008; Nordhaus, 2014). To model the limited availability of negative emission technologies (Van Vuuren et al., 2013), we impose a minimum emission level of -20 $GtCO_2$/yr. This value is based on the minimum emission levels of the scenarios in the scenario explorer for 1.5°C pathways (Huppmann, Daniel and Kriegler, Elmar and Krey, Volker and Riahi, Keywan and Rogelj, Joeri and Rose, Steven K. and Weyant, John and Bauer, Nico and Bertram, Christoph and Bosetti, Valentina and Calvin, Katherine and Doelman, Jonathan and Drouet, Laurent an, 2018) underpinning the IPCC Special Report on Global Warming of 1.5°C (Masson-Delmotte et al., 2018). Inertia is modelled by applying a constraint on the difference in CO_2 emissions between two consecutive years of 2.2 $GtCO_2$/year (based on the maximum reduction speed of the IPCC 1.5C database (Huppmann, Daniel and Kriegler, Elmar and Krey, Volker and Riahi, Keywan and Rogelj, Joeri and Rose, Steven K. and Weyant, John and Bauer, Nico and Bertram, Christoph and Bosetti, Valentina and Calvin, Katherine and Doelman, Jonathan and Drouet, Laurent an, 2018)).In every experiment, the time horizon is the year 2100, but the optimisation runs throughout the 22nd century to counter end-of-horizon problems.

The optimal carbon price is calculated using the Bellman Equation with as state variables the cumulative emissions and the capital stock, as control variable the carbon price at each time period and as objective function the discounted utility. This methodology is detailed in SI.4.2.

We distinguish between two cases: scenarios with a fixed carbon budget (or temperature target), and scenarios without target. The first case represents a cost-minimising setting while the second constitutes a traditional cost-benefit analysis. In the literature, cost-minimising analysis is typically performed using relatively detailed process models, for instance to look into the role of specific technologies or determine regional costs. In this approach it is assumed that climate targets are chosen by policy-makers in international negotiations (based on both monetary and non-monetary information). Cost-benefit models, in contrast, are typically more stylised models that determine an optimal target based on cost-optimisation (which means that all damages need to be expressed in monetary terms). The model here can be used for both types of analysis. It is also able to account for the impact of damages in cost-minimising analysis (which is typically not done).

The full mathematical formulation of the model is available in SI.4.

While there are some modelling differences between our model and DICE (e.g. different climate module, fixed investment savings rate, endogenous technological change, inclusion of inertia), the main differences reside in the calibration of the parameters.

2.4.2. Model parameters

This model allows using literature ranges on parameters relevant for global climate policy. These parameters are highlighted in colour in Figure 1.

First, the socio-economic variables like population, total factor productivity (TFP) and baseline emissions intensity are obtained from the Shared Socio-economic Pathways (SSPs, blue) (Riahi et al., 2017c).

The damage functions (green) cover the current literature range by choosing a low, medium and high damage function (see SI.1.3):

- the DICE 2016R2-damage function, representing low damages,
- the medium damage function resulting from a meta-analysis by Howard et al, which they refer to as "the preferred model for total (non-catastrophic plus catastrophic) damages". This function is based on empirical damages and traditional estimates like DICE and FUND. We refer to this damage as "Howard Total".
- the empirical damage function from Burke, Hsiang and Miguel (2015) (Burke et al., 2015). To cover the high end of damages, we use their Long Run (LR) version, which takes into account damages to the GDP growth rate based on the temperature of the 5 previous years. The GDP per capita growth losses are converted to a GDP damage function using an iterative calibration method (Glanemann et al., 2020) (see SI.1.3).

The effect of CO_2 emissions on global temperature is assumed to be linear and instantaneous through the TCRE relation (Dietz & Venmans, 2019). Based on the IPCC AR5 Working Group 1 (IPCC, 2013) relationship, we derive a value of the TCRE between 0.38 and 0.86 °C per 1000 $GtCO_2$ (5-95th percentile), with median of 0.62, equal to the range used in van Vuuren et al (2020) (Van Vuuren et al., 2020).

The MAC curve is calibrated to three levels of mitigation costs, using the consumption loss range from the IPCC AR5 Working Group 3, Fig. 6.23 (IPCC, 2014). This calibration is performed using quantile regression at the 5th, 50th and 95th percentiles to give a MAC with low, middle and high mitigation costs respectively. More information on the calibration is available in SI.1.

Finally, the utility is discounted at three pure rate of time preference values (also called utility discount rates): the low bound of 0.1%, as used in the Stern review (Stern, 2007), 1.5% and 3%. The latter two values correspond with the values used in DICE-1999 and DICE-2007 (and following versions) (Nordhaus, 2008; Nordhaus & Boyer, 2000), respectively. These values span a similar range as a recent expert elicitation of social discount rates, where the 5th and 95th percentiles of the PRTP values are 0% and 3.5%/year (Drupp et al., 2018; Hänsel et al., 2020), with an average reported value of 1.1%/year.

The effect of using a cubic, instead of a quadratic, MAC is discussed in SI.5.1, as well as the effect of using the full range of PRTP/elasticity of marginal utility combinations from the aforementioned expert elicitation (SI.7).

2.4.3. Analysing the variance using Sobol decomposition

Due to the relative simplicity of this model, we are able to calculate the optimal carbon price path (both with and without carbon budget) for every combination of parameter values shown in Table 1 (405 scenarios). This allows us to analyse the relative importance of each parameter. We quantify the contribution to the variance of each parameter with the Sobol indices (Saltelli, 2002; Sobol', 1993). These are calculated using a Monte Carlo method. This method requires a distribution for each parameter. However, sampling from a continuous distribution for each parameter would require thousands or millions of runs, which is computationally infeasible. For this reason, we approximate the distribution of each parameter by a discrete distribution best matching the normal distribution of the underlying distribution using only the parameter values available in Table 1. Since the values for the mitigation costs and the TCRE represent the 5th, 50th and 95th percentiles, the discrete distribution with equal mean and variance is a weighted distribution where the median value is 3.4 times more likely to be chosen (see Supplementary Information 4.3). A problem of this method is that the SSP, damage function and discount rate do not have an underlying distribution. To still be able to quantify the relative importance of each parameter, we associate a uniform discrete distribution to these parameters. More details of this method are available in SI.4.3.

Code availability

The full model code is available at https://github.com/kvanderwijst/DamagesAndCarbonPrice (http://doi.org/10.5281/zenodo.4555423).

Data availability

The data used for the SSP-related quantities (baseline GDP and population) are available at the IIASA SSP-database: https://tntcat.iiasa.ac.at/SspDb/. The data for each figure and underlying model runs are available at https://github.com/kvanderwijst/DamagesAndCarbonPrice (http://doi.org/10.5281/zenodo.4555423).

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Author Contributions

K.-I.v.d.W., A.H. and D.v.V. contributed to the elaboration of the model, the writing of the article and the design of the experiments. K.-I.v.d.W. developed the model code and analysis.

Supplementary Information

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New damage curves and multi-model analysis suggest lower optimal temperature

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Economic analyses of global climate change have been criticised for their poor representation of climate change damages. Here, we develop and apply aggregate damage functions in three economic Integrated Assessment Models (IAMs) with different degrees of complexity. The damage functions encompass a wide, but still incomplete, set of climate change impacts based on physical impact models. We show that with medium estimates for damage functions, global damages are in the range of 10% to 12% of GDP by 2100 in a baseline scenario with 3 °C temperature change, and about 2% in a well-below 2 °C scenario. These damages are much higher than previous estimates in benefit-cost studies, resulting in optimal temperatures below 2 °C with central estimates of damages and discount rates. Moreover, we find a Benefit-Cost Ratio of 1.5 to 3.9, even without considering damages that could not be accounted for, such as biodiversity losses, health, and tipping points.

3.1. Introduction

Cost-benefit analysis (CBA) of climate change provides insight into the economic consequences of different climate policy strategies. The results of CBAs critically depend on the quality of the underlying information on mitigation costs, avoided damages, the processes represented in the models and the coverage of relevant uncertainties. While there is a rich literature on mitigation costs (Harmsen et al., 2021; IPCC, 2014; Köberle et al., 2021; Krey, 2014; Riahi et al., 2021; Rogelj et al., 2013; Van Vuuren et al., 2020), it has been notoriously difficult to get reliable information on the damages. Similarly, much less is known about the role of the type of integrated assessment model used to analyse the costs and benefits. While model intercomparison studies are common for other climate change research areas (CD-LINKS, EMF 33, ENGAGE, NAVIGATE, REINVENT), very few have been performed on cost-benefit analyses.

In CBA models, the benefits of climate change mitigation can be obtained from reduced-form damage functions, which relate global average temperature increase to aggregate economic losses. In recent years, empirical, top-down estimates have been developed which relate observed temperature with economic growth (Burke et al., 2015; Dell et al., 2012; Kahn, Mohaddes, C Ng, et al., 2019). The disadvantage of this method is that the underlying drivers of climate damages are unknown, and it is very uncertain whether historical empirical correlations between temperature and economic growth can be extrapolated to the (far) future. In earlier CBA studies, on the other hand, most estimates of damage functions relied on semi-qualitative assessment by experts, which are currently considered mostly outdated (Bosello et al., 2021; Dellink et al., 2019; Eboli et al., 2010; Howard & Sterner, 2017; Parrado & De Cian, 2014; Szewczyk et al., 2020; Tsigas et al., 1997; Van der Wijst, Hof, van Vuuren, 2021).

To overcome these drawbacks, a new set of regional climate change damage functions (Bosello et al., 2021) were recently built in a bottom-up process as part of the European Horizon 2020 project *COACCH* (www.coacch.eu). They are based on physical impacts derived from last-generation impact models covering a wide range of sectors (agriculture, forestry, fishery, energy demand, energy supply, labour supply, riverine floods, transportation, and sea-level rise) (Bosello et al., 2021). The impact of these physical damages on economic losses were estimated by an economic model: the Computable General Equilibrium (CGE) model (Dellink et al., 2019; Szewczyk et al., 2020; Tsigas et al., 1997) ICES (Parrado & De Cian, 2014) with improved representation of driving forces and transmission mechanisms of economic impacts (Fig. 1 and Extended Data Table 1).

Compared with similar exercises (Dellink et al., 2019; Eboli et al., 2010; Szewczyk et al., 2020), the damage functions developed here use a higher level of regional detail and provide internally consistent uncertainty ranges. This high spatial granularity applies particularly to the EU, where the macroeconomic impact assessments are determined at the NUTS2 level.

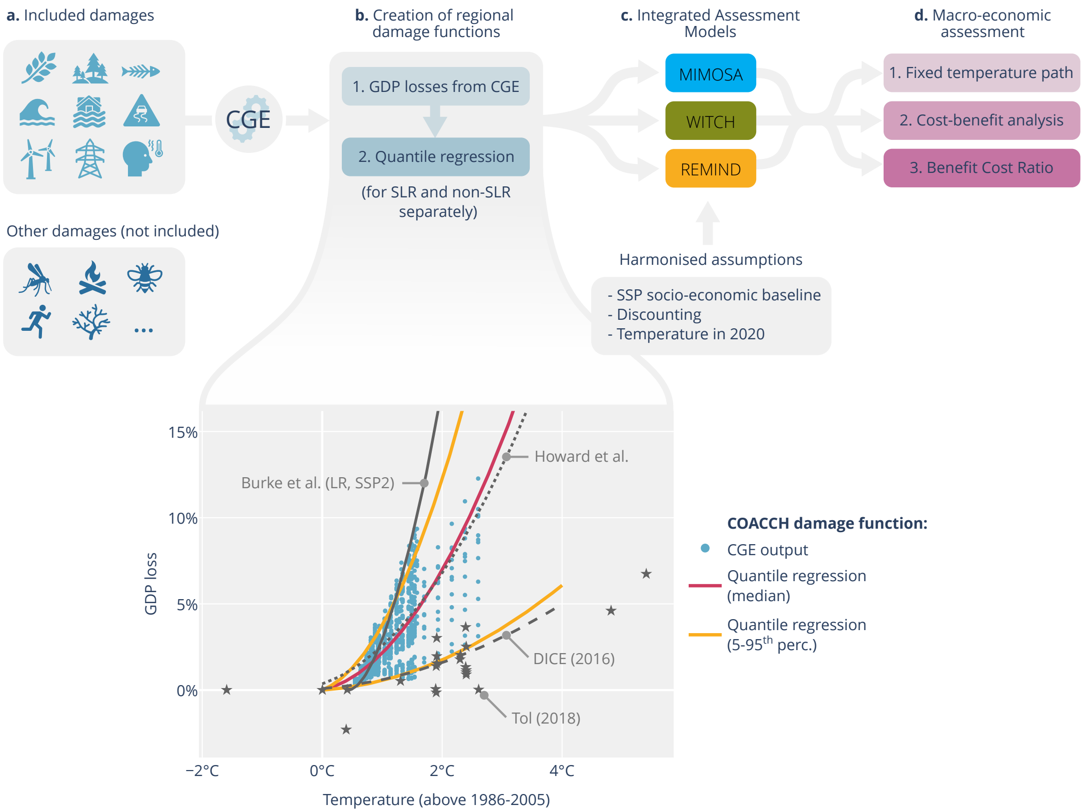


Figure 1. Overview of the creation and use of the damage functions. *Results from 9 sectoral impact models are included in a CGE model to calculate GDP losses for various scenarios and points in time. Using quantile regression, a curve is fitted through the points at the 5th percentile (low estimate), 50th percentile (medium) and 95th percentile (high), for each region. These reduced form damage functions are used in the Integrated Assessment Models for the macroeconomic analysis of this paper. The example damages shown in the bottom panel are the combined damages (including sea-level rise, no adaptation) aggregated for the world, and are compared to several literature damage estimates.*

The consistency in uncertainty representation derives from accounting for i) different climate scenarios, ii) different socio-economic scenarios, iii) different impact ranges within each climate scenario originated by impact model uncertainty, and, finally, iv) how the economy reacts to these impacts. The new damage functions have been separately estimated for impacts related to temperature increase and sea-level rise (with a much longer time delay). The damage curves also include versions for the case of sea-level rise with and without optimal adaptation (see Methods).

Literature shows that the results of cost-benefit studies depend not only on the damage function but also on the macroeconomic parameters and assumptions like discounting or savings, as well as the representation of mitigation costs and dynamics (Van der Wijst, Hof, van Vuuren, 2021). Several studies have been published in recent years looking into uncertainty in cost-benefit analysis. These studies typically only consider a single model (Glanemann et al., 2020; Hänsel et al., 2020; Rennert et al., 2022; Van der Wijst, Hof, van Vuuren, 2021) and use the older top-down or empirical damage functions. Here, we perform the first multi-model CBA study using the newly developed COACCH damage functions, allowing to explore the impacts of a consistent set of damage curves (including an explicit uncertainty estimate) in different models. Three IAMs are used: the reduced form model MIMOSA (Van der Wijst, Hof, van Vuuren, 2021), and the process-based models WITCH (Emmerling et al., 2016) and REMIND (Baumstark et al., 2021). First, we investigate how the damage functions translate to (regional) GDP losses given different temperature pathways and how the results from each model relate to each other (so covering the uncertainty as result of model representation). Next, we determine the combined effect of mitigation costs and damages on optimal emission pathways using cost-benefit analysis and compare them with the goals of the Paris Agreement (Fig. 1). We also calculate Benefit-Cost Ratios (BCRs) for these optimal emission pathways, which indicates the relationship between the relative costs and benefits of climate mitigation. For medium estimates of damage function and discount rate, we find a BCR of 1.5 to 3.9. This presents an important case to improve societal acceptance of climate policy, as the purely economic benefits of reduced climate damages significantly outweigh the costs of climate policy.

3.2. Multi-model comparison of economic damages

We first compare the sensitivity of final economic damages to different model dynamics. To do this, we calculate the macro-economic effect of the damage functions in the three IAMs under two fixed temperature pathways: the Representative Concentration Pathway (Van Vuuren, Kriegler, et al., 2014) (RCP) 6.0 leading to a global average temperature change of about 3°C by 2100 (also coinciding with the no-policy scenario in one of the models, REMIND), and RCP 2.6, which is a trajectory in line with the well below 2 °C target of the Paris Agreement, i.e. RCP 2.6. We fixed the temperature pathways to reveal whether the model parameterisations shaping the economic growth differ substantively.

The COACCH functions allow decomposing the total GDP losses into (i) direct impacts from sea level rise, (ii) direct temperature-related impacts and (iii) indirect impacts from cumulated dynamic effects, e.g. through investment (Fankhauser & Tol, 2005; Kikstra et al., 2021). Unless stated otherwise, we assume that optimal adaptation has taken place against sea-level rise (SLR) damages. Therefore, reported SLR damages are the sum of SLR adaptation costs and residual damages.

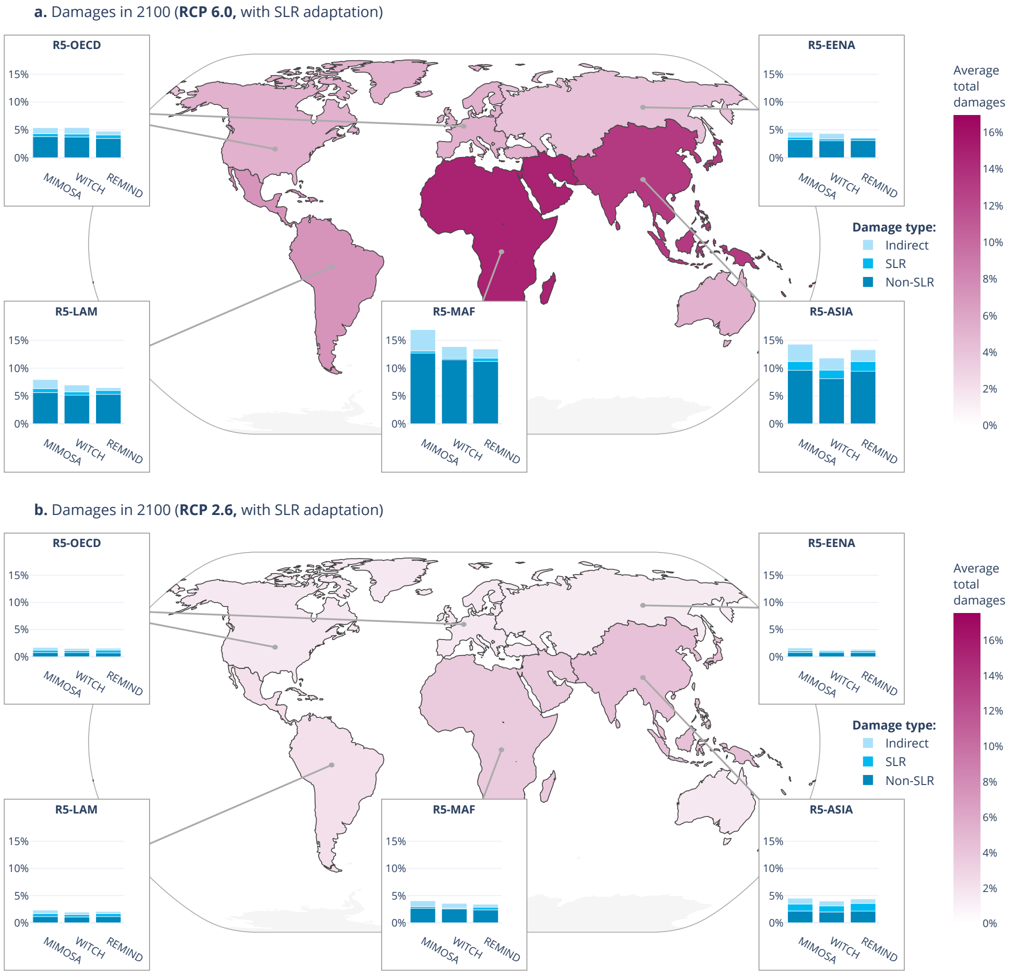


Figure 2. End-of-century damages for the 5 macro-regions for two scenarios. *The damages are split in three damage types (direct temperature related damages, direct sea-level rise damages and indirect damages from GDP loss accumulation). The damages are shown for the year 2100 in (a) the RCP6.0 scenario and (b) the RCP2.6 scenario. Both scenarios assume optimal sea-level rise adaptation. This figure does not show intra-regional differences; only the population-weighted average per macro-region is shown.*

On a global level, the GDP loss in the baseline RCP 6.0 scenario ranges from 10 to 12% at the end of the century when using medium damage (50th damage quantile) estimates. The damages are significantly reduced in the mitigation scenario RCP 2.6 to 3.1-3.6% GDP loss in 2100. The economic damages are not very sensitive to the model used.

In Fig. 2, higher spatial resolution results from the original COACCH damage functions and the IAM used have been aggregated for the five macro-regions of the SSP database (Riahi et al., 2017a) to facilitate comparison (see Methods).

There is high agreement across models also on regional damage patterns, although the ranges are larger in some regions than others. In the RCP 6.0 scenario (Fig. 2a), the damages are the highest in the Middle East and Africa region, with total losses between 13% and 18% of GDP, followed by 12% to 14% for Asia. The other three regions have lower total damages (6-8% for Latin America, 5% for OECD and 3-5% for Eastern Europe and Northern Asia). This figure does not show intra-regional differences; only the population-weighted average per macro-region is shown.

Even with optimal adaptation, sea-level rise damages, including adaptation costs, make up a significant part (10-13% of total direct damages) in Asia and the OECD region. This share is much lower in the other regions (as low as 2% of total direct damages for Africa). Without sea-level rise adaptation (Fig. SI.1.1), total damages per region become substantially higher (from global average damages of 11-12% with SLR adaptation to global damages of 14-17% without SLR adaptation). This is especially pronounced in the OECD (5-6% total damages with SLR adaptation to 12% total damages without SLR adaptation), which confirms previous literature on the benefits of SLR adaptation (Schinko, Drouet, Vrontisi, Hof, Hinkel, Mochizuki, Bosetti, Fragkiadakis, Van Vuuren, et al., 2020).

RCP 2.6 reduces the total damages to a regional maximum of 4.5%, compared to the 18% for RCP 6.0 (Fig. 2b). The regional distribution of damages is similar to RCP 6.0, except that Asia has now slightly higher damages than Africa. Because of the slow processes of sea-level rise, the differences in sea-level rise damages between RCP 2.6 and RCP 6.0 are relatively small in the first half of the century. Accordingly, the relative share of damages from sea-level rise becomes larger, especially in regions with relatively long coastlines, like Asia and the OECD. Without SLR adaptation, Asia and the OECD have the highest damages in RCP 2.6, as, in that case, sea-level rise damages account for most of the total damages (Fig. SI.1.1b).

3.2.1. Impact of damage curve uncertainty

The total damages are significantly higher when using the high end of the damage quantile (95th damage quantile, see Methods): 18-22% global average GDP loss instead of 11-12% for the medium damage quantile (Fig. 3). There is a small probability that global impacts are slightly positive up to 2050, indicated by negative GDP losses for the 5th damage quantile, due to significant gains in Latin America from increased agricultural yield (see Fig. SI.1.4b). These gains are offset by sea-level rise damages towards the end of the century.

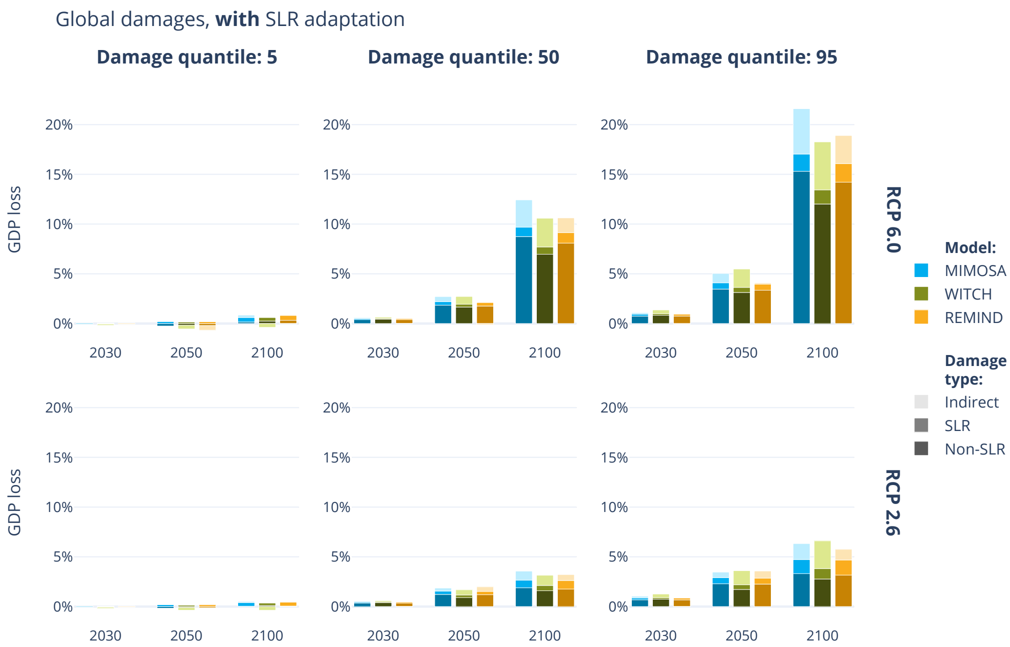


Figure 3. Sensitivity analysis of the global damage costs. *Damage cost decomposition of the global GDP losses with optimal sea-level rise adaptation for RCP 6.0 (top row) and RCP 2.6 (bottom row) for three levels of damages (low: 5th quantile, medium: 50th quantile, high: 95th quantile), in 2030, 2050 and 2100.*

Until 2050, the differences between RCP 2.6 and 6.0 are still moderate. They only strongly diverge towards 2100 (up to 50% higher damages in RCP 6.0 than RCP 2.6 in 2050, whereas the damages are 300% higher towards the end of the century).

REMIND shows lower indirect effects than the other models. While in MIMOSA and WITCH all economic assets are fixed, in REMIND, assets can be relocated, facilitated by more advanced trade mechanisms (Leimbach & Bauer, 2021), and, accordingly, losses are lower.

3.3. Cost-benefit analysis

We now add mitigation costs of each model to perform a comprehensive CBA.

The cost-optimal (or, in a strict sense, welfare-optimal) end-of-century temperature for the medium estimates of damages is similar for all three models: around 1.9°C above pre-industrial levels (Fig. 4). These temperature estimates are median climate estimates; we have not assessed uncertainty in the climate module. Interestingly, none of the models applies net-negative emissions to limit temperature increase to these levels. This is a consequence of running the models in cost-benefit mode (minimising damages and mitigation costs) instead of cost-effectiveness mode (minimising mitigation costs only). Previous (Schultes et al., 2021; Van der Wijst, Hof, van Vuuren, 2021; Van der Wijst, Hof, Van Vuuren, 2021) research has shown that cost-benefit runs lead to much higher reductions early in the century and less use of net-negative emissions than cost-effectiveness runs.

As expected, the low damage function leads to higher optimal end-of-century temperature increases of 2.8-3.1°C, and the higher end of the damages leads to optimal temperature increases, which are very close to the 1.5 °C target of the Paris Agreement (1.5-1.7°C).

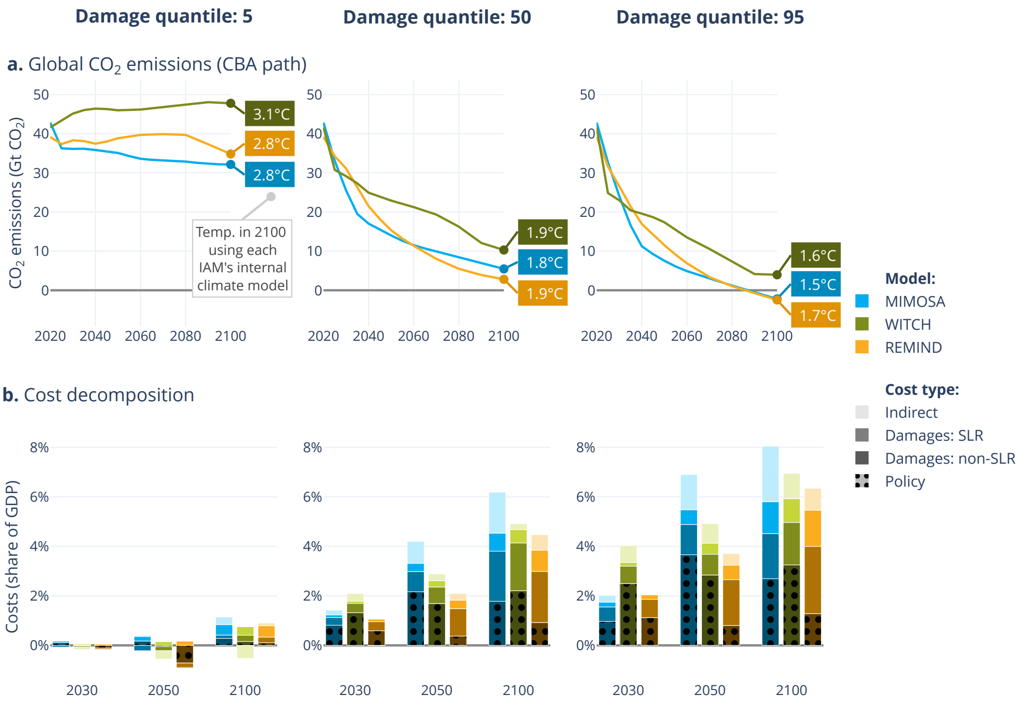


Figure 4. Emission pathways, damage costs and climate policy costs in cost-benefit (CBA) setting. *(a) Cost-optimal emission trajectory and corresponding end-of-century temperature in cost-benefit runs for the low, medium and high end of the damage function uncertainty range (damage quantiles). While only global CO2 emissions are shown in this figure, each model takes into account non-CO2 gases as well in their calculation of temperature outcomes. (b) GDP loss (compared to baseline GDP) decomposed in policy costs (mitigation costs), damage costs and indirect costs. Here, the indirect costs result from accumulated GDP impacts from mitigation and damage costs.*

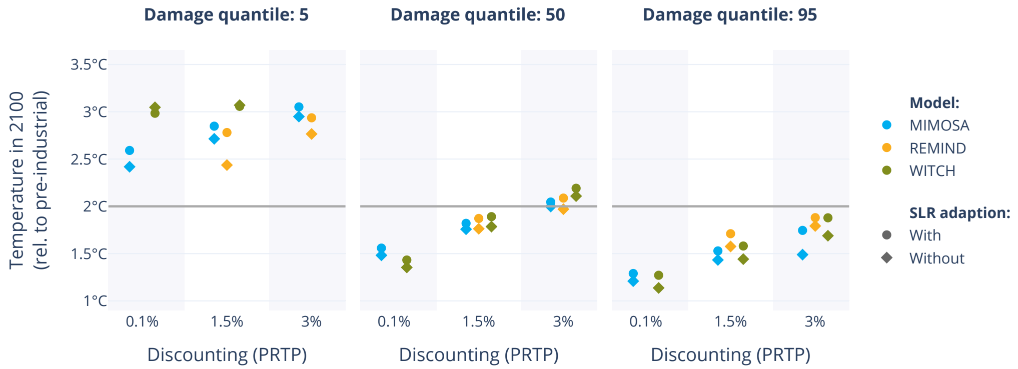


***Figure 5. Optimal temperature in 2100 in CBA** for different levels of discounting and SLR adaptation assumptions. The levels of discounting are quantified by three values of the Pure Rate of Time Preference (PRTP), also called utility discounting. REMIND has not been calibrated to use the low utility discount rate.*

3.3.1. Model uncertainty

The optimal emission pathways in MIMOSA, WITCH and REMIND are similar. REMIND is slightly less sensitive to variability in the damage function than the other two models. It can be also noted that overall mitigation costs are lower in REMIND (Fig. 4b, see also (Harmsen et al., 2021)). Nonetheless, in terms of temperature, the model shows the smallest difference (only 0.2°C) between the 50th and 95th damage quantile. The bottom-up description of mitigation options, including hard-to-abate processes, puts stringent constraints on the total mitigation potential; this means that the model already exploits the largest share of the total mitigation potential already in the 50th damage quantile run. In MIMOSA, the mitigation costs are higher (around 2% of GDP for the medium CBA scenario) than REMIND, but the model is more flexible in achieving higher mitigation levels. It has less strict inertia constraints and allows more net-negative emissions towards the end of the century than REMIND or WITCH, explaining the lower optimal end-of-century temperature in the high damage quantile scenario. WITCH shows a stronger initial mitigation effort and less towards the end of the period, even with the modest global carbon price of \$67/tCO_2 in 2030 (see Fig. SI.2.1) for medium damages. WITCH still reaches similar end-of-century temperatures as REMIND and MIMOSA, based on different assumptions about land-use CO_2 emissions, other greenhouse gases, and the climate model used.

3.3.2. The role of discounting

Another key component in long-term cost-benefit analysis is the discount rate. By default, we use a pure rate of time preference (PRTP) of 1.5%/year, combined with an elasticity of marginal utility of 1, in line with recent literature (Hänsel et al., 2020; Van der Wijst, Hof, van Vuuren,

2021) and a recent expert elicitation (Drupp et al., 2018). We perform a sensitivity analysis with a lower and higher discounting parameter to cover the full range of current discounting estimates. We use 0.1%/year as a low PRTP value, as in the Stern (Stern, 2007) review, and 3%/year as a high PRTP value covering a range similar to the Inter-Agency Working Group on the Social Cost of Carbon (IAWG, 2010), while keeping the elasticity of marginal utility fixed.

As shown in Fig. 5, the impact of damage function uncertainty on the cost-optimal end-of-century temperature is twice as large as the impact from discounting uncertainty. The spread in optimal temperatures is around 1.5°C for damage cost uncertainty and 0.7°C for uncertainty in discounting. Without sea-level rise adaptation, the optimal temperature is, across all discounting scenarios, between 0.1°C and 0.2°C lower than with optimal sea-level rise adaptation, as the models choose to reduce the other damages as much as possible. Only for end-of-century temperatures of 1.5°C or lower, peak temperatures are in some cases more than 0.1°C higher than 2100 temperatures (see Suppl. Fig. 2.2).

3.3.3. Comparing costs to avoided damages using the Benefit-Cost Ratio

Besides providing a cost-optimal target, an important and policy-relevant metric is the Benefit-Cost Ratio, showing by how much the avoided damages outweigh the mitigation costs. When subtracting the residual damages of a CBA scenario from the damages in a baseline scenario, we obtain the avoided damages, or, in other words, the economic benefits of mitigation (expressed as % of GDP). Comparing the total discounted avoided damages to the total mitigation costs gives a Benefit-Cost Ratio of mitigation (Extended Figure 1). Globally,

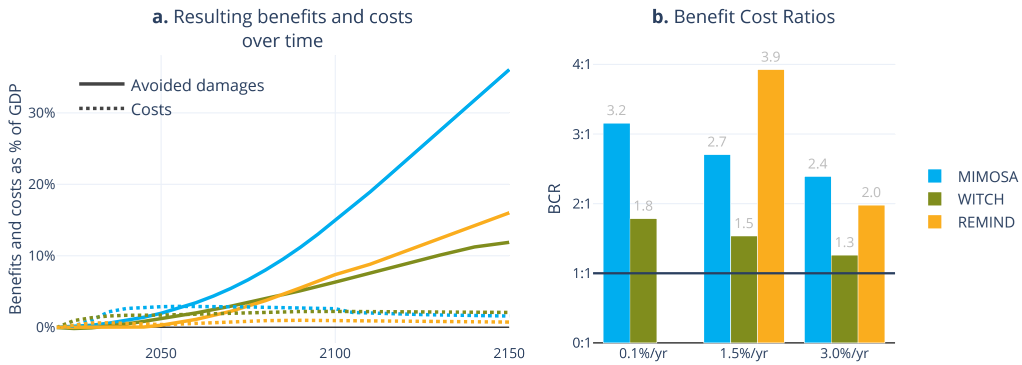


Figure 6. Benefit-cost ratio for the CBA scenario *using the medium damage function (50th percentile). Left: policy costs (dotted lines) and avoided damages (benefits, solid lines) over time for the scenario with medium discounting. Right: Benefit-Cost Ratio (BCR): total discounted avoided damages divided by the total discounted mitigation costs. REMIND is not calibrated for the lowest discount rate.*

most benefits occur in the second half of the century or even beyond 2100, as damages increase slowly while mitigation costs increase early, even incurring the large costs at the beginning of the transformation. Therefore, we consider the 2020-2150 time range. Using a medium discount rate (pure rate of time preference of 1.5%/yr), the benefits are almost twice the total discounted costs (multi-model range of 1.5 to 3.9, Fig. 6). This gives strong economic validation of the Paris-consistent mitigation scenario, especially when considering that the damage functions are likely to be underestimates since not all damage sectors have been included (see Discussion). When assuming the high damage function, the benefit-cost ratio increases to 1.8 - 5.0 for medium discounting (Figure SI.2.2.). Since the low damage function yields CBA paths with very low to no mitigation effort, the BCR is not calculated here. Since these scenarios are performed in a cooperative setting, only the global results are calculated. A regional BCR requires assumptions on equity and burden sharing, which are outside the scope of this paper (see Discussion).

3.4. Discussion

The results in this study show that, from a purely economic perspective, the benefits of reduced climate damages significantly outweigh the costs of climate policy, even when some climate change damages, including those on biodiversity and health, are not accounted for. This presents an important case to improve societal acceptance of climate policy.

The results are based on i) detailed process-based biophysical impacts, ii) a consistent economic modelling approach to quantify and monetise these impacts in a multi-model context, iii) the separation of temperature and sea-level rise impacts, and iv) allowing for sea-level rise adaptation investment. We show that with medium damages (evaluated at the median of our multi-impact-model chain estimated damage function), the optimal temperature increase is below 2°C according to all three models. Assuming the high end of the damage function (estimated at the 95th percentile), the optimal temperature increase is close to 1.5°C in all three models. Since the COACCH damage functions do not include all impacts (e.g. biodiversity loss, health impacts and tipping points), the resulting temperature outcomes are likely to be conservative, meaning that this study gives strong economic validation of the Paris Agreement. Our damage functions only explicitly modelled adaptation for sea-level rise. For the other impacts, adaptation is implicitly addressed in the CGE (market-driven adaptation), but not in the impact models. Future research needs to improve our understanding of adaptation in a comprehensive global impact study.

Interestingly, when aggregated globally, the COACCH low, medium and high damage functions are close to, respectively, the DICE (Nordhaus, 2014), Howard et al. (Howard & Sterner, 2017) and Burke et al. (Burke et al., 2015) functions (see Fig. 1.), thus also leading to similar optimal temperature levels22. However, the methodology for creating the damage function is completely different. While DICE, just like the new functions presented here, also relies on bottom-up sectoral physical impacts, major criticisms about these damage functions (as used in DICE (Nordhaus, 2014), FUND (Anthoff & Tol, 2014) and PAGE (Hope, 2013)) are the lack of empirical foundation, the relatively simple monetisation method used, and that they are based on relatively old and scarce impact data (Pindyck, 2019, 2020). A more recent study (Rennert et al., 2022) with bottom-up impacts directly included damages from a limited set of 4 sectors in their IAM using a simplified damage function for each of the sectors. Contrary to the bottom-up methods like DICE and Rennert et al (2022) (Rennert et al., 2022), empirical damage functions, like Burke et al., with their "reduced-form nature" constitute black boxes: the underlying impact drivers are unknown, which makes it far from certain that these historical correlations between temperature and economic growth also hold for the (far) future (Bosello & Parrado, 2020; Piontek et al., 2021). With the advancement of sectoral physical impact models, the COACCH damage functions rely much less on semi-qualitative expert assessment and avoid simple monetisation by translating the state-of-the-art physical impacts into economic damages using a CGE. This improves the transparency of how each type of physical impact is implemented in the economical assessment (see Table SI. 3.1). However, more research should be performed to monetize and include more climate impact sectors, like biodiversity losses, health impacts and tipping points.

Apart from the results of the CBA, the regional macro-economic implications of the new COACCH damage functions show equally important insights. While there is a lot of attention regarding the regional distribution of mitigation costs (Höhne et al., 2013; X. Pan et al., 2014; Raupach et al., 2014; van den Berg et al., 2020), this research shows that financing loss and damages is just as important, since even Paris-compliant scenarios still yield significant damages, especially in developing regions. While the new damage functions provide improved estimates of economic climate damages on a regional level (as shown in Fig. 2), the Benefit-Cost Ratios provided in this study are only applicable on a global scale. A regional BCR would imply specific assumptions about regional equity regarding the distribution of mitigation costs, like burden sharing regimes and emission trading schemes (Bauer et al., 2020; van den Berg et al., 2020), which are outside the scope of this study.

In this research, we have not taken all possible uncertainties into account. We have instead concentrated on the two main sources of uncertainty in CBA: damage costs and discounting, together accounting for almost 75% of total variance in cost-optimal temperature variance according to a recent CBA study (Van der Wijst, Hof, van Vuuren, 2021). Other relevant sources of variance are mitigation cost uncertainty, climate uncertainty and socio-economic uncertainty. By systematically using three different IAMs, this study considers between-model uncertainty in mitigation costs and climate model, but not within-model uncertainty.

An extra source of uncertainty originates from the separation between sea-level rise damages and purely temperature related damages. While all three models considered in this study have the ability to separate the two by modelling sea-level rise explicitly, this is not the case for all IAMs. For this reason, the new damage functions are also provided as combined damage functions depending only on temperature (SI.3.2c). These functions include the aggregated effect of SLR and non-SLR damages. They result in similar damages for high temperature

Climate change impact area	Impact model sourcing data	Variable	Modelling implementation for the economic assessment
Agriculture	EPIC biophysical model[47] and GLOBIOM model[48], updated in 2021	(Change in) Crop yield	Changes in the productivity of the "land input" to the regional agricultural sectors
Forestry	G4M model[49]	(Change in) Net physical wood production per hectare	Changes in the productivity of the "natural resource" input to the regional timber industries
Fishery	DBEM envelope model[50] and DSFM food web model[51]	(Change in) Fish catches	Changes in the productivity of the "natural resource" input to the regional fish industries
Sea-level rise	DIVA model[52]	- Annual land loss due to submergence - Expected annual damages to assets - Expected annual number of people flooded - Annual protection costs (for the adaptation scenario)	- Changes in land input available to the regional agricultural sectors - Changes in the capital stock available to regional economies - Changes in the productivity of the labour input - Opportunity cost of capital (lower capital stock, and lower damages for the adaptation scenario)
Riverine floods	GLOFRIS model[53]	- Expected annual damages for the industrial, commercial, and residential sectors - Expected annual number of people flooded	- Changes in the capital stock available to regional industrial, commercial, building sectors - Changes in the productivity of the labour input
Road transportation	OSDaMage model[54]	Expected annual damages for the road infrastructure	Change in the total factor productivity of the regional road transportation sector
Energy supply	Schleypen et al., (2019)[55]	Changes in wind and hydropower production	Change in the total factor productivity of the regional wind and hydro energy sector
Energy demand	Scheypen et al., (2019)[55]	Changes in energy demand by households and by the industrial, agricultural and service sectors for coal, oil, gas, electricity	- Changes in energy demand by the regional household - Changes in productivity of energy input for the macro sectors
Labour productivity	Dasgupta et al., (2022)[56]	Changes in per capita production of value added	Changes in regional labour productivity

Extended Data Table 1. Impacts categories *included in the estimation of the reduced-form climate change damage functions and implementation for their economic assessment.*

scenarios (RCP 6.0, see Suppl. Fig. 1.2). However, the combined damages are up to 50% lower than the disaggregated damage functions in an RCP 2.6 scenarios without SLR adaptation (Suppl. Fig. 1.2), due to the different time scales that are not being captured when SLR is not modelled explicitly. This highlights the importance of separating sea-level rise damages from other temperature-related damages.

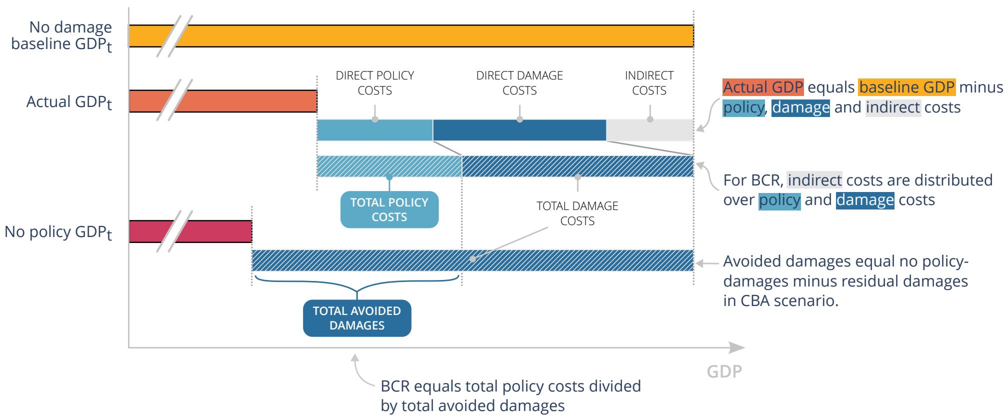
This analysis shows the importance of including the full range of damage function uncertainty, as this strongly influences possible policy recommendations. It also highlights that different models can lead to different results. Using multiple models can highlight these differences and lead to more robust outcomes in the case of model agreement. While the uncertainty due to three models in the cost-optimal end-of-century temperature is much smaller than the damage and discounting uncertainty, the model range in the Benefit Cost Ratio does show the importance of including multiple models in a cost-benefit analysis.

3.5. Methods

3.5.1. Damage functions

Damage functions connect global or local temperature increase to loss of income or consumption. Here, we use the newly created COACCH damage functions.

In a first step a set of climate change damages quantified by process-based sectoral impact



Extended Data Figure 1. Calculation of the costs and the benefits (avoided damages) for the Benefit-Cost-Ratio analysis. *First, the direct policy and residual damage costs are scaled to include the indirect costs (remaining difference with a baseline run without damages). The scaled residual damages are subtracted from the total damages from a no-policy run.*

models have been evaluated in their macroeconomic consequences applying the ICES recursive-dynamic computable general equilibrium model (Parrado & de Cian, 2014) (www.icesmodel.org). The list of impacts considered and their implementation in the CGE model for the evaluation are reported in Extended Data Table 1. The climate change impacts do not include potential losses originated in ecosystems or in the health sector. This is motivated by the difficulty to address with a "market-transaction-based" model like a CGE, the non-market dimension of those impacts. Also, catastrophic events are not considered, even though some "extremes" (riverine floods) are included.

To provide the amplest account for uncertainty, all the impacts have been specified for 9 combinations of climate change scenarios (RCPs), social economic development scenarios (SSPs) (see Fig. SI.3.1) between 2020 and 2070, a range of low-to-high variability in the climate and impact models used and two different assumptions on investment mobility determining the economic consequences.

In a second step, these data are used to extrapolate the reduced-form climate change damage functions. Two different types of damage functions have been estimated using linear and quadratic quantile regression, depending on the region (see SI.3.1). One specific to sea-level rise (SLR); the other to the remaining climate change damages. SLR damage functions have been estimated assuming "current level adaptation" and "incremental adaptation", when coastal protection upgrades following the prescription of "optimal" adaptation from the DIVA model (Lincke & Hinkel, 2018). For the remaining damages, adaptation is not explicitly modelled. However, some level of adaptation occurs in the CGE optimization process, where economical assets can be reallocated between sectors and regions. All damage functions and underlying GDP loss estimates are provided in SI.3.1. The damage functions have been estimated through different damage quantiles. Unless otherwise stated, the medium damage estimate is the 50th quantile, with the low and high estimates respectively the 5th and 95th quantile.

3.5.2. Direct vs. indirect costs

The COACCH damage functions are level damage functions: they directly impact economic output, instead of economic growth. However, a reduced economic output also has an indirect impact on GDP growth (Kikstra et al., 2021) through reduced investments for the next time period. For this reason, we also report indirect damages, accounting for this reduced growth effect. When fixing the temperature path to RCP6.0 or RCP2.6, we calculate the indirect damages as the difference between an RCP run with and one without damages, while keeping the mitigation costs constant. This yields the total damages. By subtracting the direct damages as reported from the damage function, we obtain the indirect damages. For the CBA runs, it is not possible to distinguish between reduced economic growth from climate impacts and from mitigation costs. We therefore do not report the indirect damages, but the combined indirect costs from both damages and policy costs. These are calculated as the difference between in GDP between the CBA run and a baseline without damages and without mitigation costs. By subtracting both the direct damages and the mitigation costs, we obtain the combined indirect costs. For the Benefit-Cost Ratio calculation, the indirect costs need to be included for a fair comparison of benefits and costs. We therefore scale the direct policy and residual damage costs to include the indirect costs to obtain total policy and residual damage costs. The residual damages are then subtracted from the total damages in a no-policy scenario (Extended Fig. 1).

3.5.3. Integrated Assessment Models

To assess the macro-economic implications of the new COACCH damage functions, we use three different IAMs of varying levels of complexity. IAMs are models designed to capture the interplay between, among others, the climate, the economy and the energy system.

MIMOSA (Van der Wijst, Hof, van Vuuren, 2021) is a recent IAM based on FAIR (Den Elzen & Lucas, 2005), with 26 regions covering the whole world. It is a relatively simple Cost-Benefit IAM but still covers the relevant technological and socio-economic dynamics. Temperature is a linear function of cumulative CO_2 emissions (Dietz & Venmans, 2019). MIMOSA uses the DICE sea-level rise module. In contrast with the previous global version, we have now regionalized the mitigation costs, population, initial capital stock and baseline GDP and CO_2 emissions (see SI.4 for more details). The direct regional mitigation costs are calculated as area under the Marginal Abatement Cost (MAC) curve, and have been recalibrated to the IPCC AR6 WGIII database.

WITCH (Emmerling et al., 2016) is a dynamic optimisation IAM of intermediate complexity, with 17 world regions. The climate module is based on the DICE and MERGE climate modules, calibrated to reproduce the CMIP5 model ensemble results. The sea-level rise module is the model of Li et al. (2020) (Li et al., 2020). Mitigation costs are endogenously computed based on a fully hard-linked energy system covering all main energy supply technologies and demand sectors. Moreover, land-use mitigation actions and costs are computed based on the linked GLOBIOM model. The policy costs are then calculated as total GDP loss compared to a baseline scenario without climate policy.

REMIND (Baumstark et al., 2021) is an optimal growth IAM with a high level of detail in the representation of the economy and the energy sector including mitigation options in the energy system and land-use sector. REMIND is soft-coupled to MAGICC (Meinshausen et al., 2011) as its climate module. The policy costs are calculated as GDP losses compared to a baseline scenario without climate policy.

3.5.4. The Computable General Equilibrium model

ICES (Parrado & De Cian, 2014) is a recursive dynamic computable general equilibrium (CGE) model for the world economy based on the GTAP 8 database (Narayanan et al., 2012). While, at the time of writing, GTAP10 is available, ICES has been calibrated separately for the entire 2020-2070 period according to the macroeconomic trends of the SSPs, making it less sensitive to updates of the starting point (more recent calibration years) from the newer GTAP versions. It simulates in 5-year time steps from 2020 to 2070. For this exercise, a model version has been developed featuring a sub-national resolution for the EU economies represented by 138 territorial units. 24 different economic sectors are considered. An extended description of the ICES model and of the calibration process is provided in SI.6. Using a CGE to calculate the damages allows to use the highly detailed representation of the economy to account for feedbacks and rebound effects triggered by climate change impacts.

3.5.5. Harmonisation

To allow a comparison of the results between the models, we harmonise key assumptions. We use the SSP2 (Riahi et al., 2017b) assumptions on baseline GDP and population growth and baseline emissions. The discounting is also harmonised: by default, we use a Pure Rate of Time Preference (PRTP, also called utility discount factor) of 1.5%/year and an elasticity of marginal utility of 1.001, in line with a recent expert elicitation (Drupp et al., 2018) on discount rates. Since temperature is an essential factor determining the climate damages, the climate models are calibrated such that the 2020 temperature is harmonised and equal to 1.16°C above pre-industrial levels (Visser et al., 2018). Moreover, all damages are reported relative to 2020 damage levels. While the COACCH damage functions are calibrated for the 1986-2005 period and therefore report non-zero damages in 2020, we assume that the observed GDP of 2020 already incorporates these damages. Specifically, if the COACCH damage function relative to 1986-2005 temperature is noted by $D_{1986-2005}(T_t)$ for temperature level T_t, the damages as incorporated in the models are:

$$D_{\text{rel. to 2020 level}}(T_t) = D_{1986-2005}(T_t) - D_{1986-2005}(T_{2020}),$$

where T_{2020} is the global mean temperature in 2020.

Finally, since each model uses different regional definitions, we aggregate all results to the five macro regions of the SSP database (Riahi et al., 2017a) (see https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about#regiondefs for the detailed country mapping of each region):

- ASIA: most Asian countries, except for the Middle East, Japan, the Russian Federation, Central Asia and the Caucasus region
- EENA: Eastern Europe and North Asia: Russian Federation, Belarus, Ukraine, the Caucasus region, Central and North Asia
- LAM: Latin America
- MAF: the Middle East and Africa

- OECD: includes all OECD and EU countries except Egypt, Israel, Mexico and South Korea. Also includes Albania, Bosnia and Herzegovina, Bulgaria, Guam, Macedonia, Montenegro, Puerto Rico, and Serbia

While these key assumptions have been harmonised across the three IAMs, the models differ, among others, in their representation of the economy, their internal climate and sea-level rise module, and the energy sector.

Data availability

All regional damage coefficients for the reduced-form climate change damage functions are available at https://zenodo.org/record/5546264#.YlWeBehBw2w. This includes the sea-level rise, non-sea-level rise and combined damage functions for all used damage quantiles. All scenario data from the three models is available at https://doi.org/10.5281/zenodo.7627679.

Code availability

The calculations and the figures used in this paper and the scripts required to reproduce them are available at https://doi.org/10.5281/zenodo.7627679.

The model code and documentation of the MIMOSA model is available at https://github.com/kvanderwijst/Project-MIMOSA/, of the WITCH model at https://www.witchmodel.org/ and of the REMIND model at https://rse.pik-potsdam.de/doc/remind/2.1.0/ and https://github.com/remindmodel/remind for the model code.

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Author contributions

All authors contributed to the manuscript, the development of the idea and set up of the study. FB, RP, GS, SD and KvdW developed the damage functions. FB, LD, JE, AH, ML, FP, DV and KvdW developed and ran the CBA scenarios. KvdW performed the multi-model analysis.

Supplementary Information

The supplementary information is available online at:

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Costs of avoiding net negative emissions under a carbon budget

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The 2°C and 1.5°C temperature targets of the Paris Agreement can be interpreted as targets never to be exceeded, or as end-of-century targets. Recent literature proposes to move away from the latter, in favour of avoiding a temperature overshoot and the associated net negative emissions. To inform this discussion, we investigate under which conditions avoiding an overshoot is economically attractive. We show that some form of overshoot is attractive under a wide range of assumptions, even when considering the extra damages due to additional climate change in the optimisation process. For medium assumptions regarding mitigation costs and climate damages, avoiding net negative emissions leads to an increase in total costs until 2100 of 5% to 14%. However, avoiding overshoot only leads to some additional costs when mitigation costs are low, damages are high and when using a low discount rate. Finally, if damages are not fully reversible, avoiding net negative emissions can even become attractive. Under these conditions, avoiding overshoot may be justified, especially when non-monetary risks are considered.

4.1. Introduction

At the 21st Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCC) in 2015, 174 countries ratified the Paris Agreement. They agreed to limit global mean temperature change to well below 2°C and pursue efforts to stay below 1.5°C above pre-industrial levels. Different interpretations of such temperature targets can be found in the literature, i.e. either a value that can never be exceeded or something that needs to be achieved this century (allowing a temporary overshoot). Given the near-linear relationship between CO_2 emissions and global temperature change, the former translates into a peak carbon budget, i.e. the cumulative net CO_2 emissions until net-zero CO_2 emissions is reached. In contrast, the latter translates into a net carbon budget during the 21st century (in both cases assuming an equivalent reduction of non-CO_2 greenhouse gas emissions). Many of the scenarios developed by Integrated Assessment Models (IAMs) used in the fifth assessment report of the IPCC followed the second approach: first, they exceeded the carbon budget (for a short period), after which the excess emissions were compensated by net negative emissions towards the end of the century (IPCC, 2014; Van Vuuren et al., 2013). In response, there has been a lively debate in the literature about both the risks related to (net) negative emissions and the allowance of overshoot (Fuss et al., 2018; Van Vuuren et al., 2017).

In this context, Rogelj et al. (Rogelj et al., 2019) proposed to replace the end-of-century budgets with so-called peak budgets. Interestingly, in their proposal, little consideration was given to the related costs and benefits of avoiding net negative emissions. On the one hand, avoiding overshoot avoids the extra damages from climate change incurred throughout the century as a result of exceeding the temperature target. On the other hand, it also leads to less flexibility in the timing of mitigation, leading to higher mitigation costs (up to 80% higher in current IAM literature scenarios (Hilaire et al., 2019)). In this paper, we fill this gap by investigating the net effect of these opposite economic impacts of avoiding overshoot. More specifically, we determine under which conditions peak budgets might be an attractive strategy from an economic perspective and under which conditions it would not be.

The answer to these questions depends on several factors, such as the severity of damages, discount rate, climate sensitivity, and mitigation costs. We perform a sensitivity analysis covering the literature ranges for each of these factors to investigate the economic effect of the decision not to allow overshoot – therefore providing evidence of the rationality of such a choice based on abatement costs and damage costs. This informs the debate about the (dis)advantages of net negative emissions. It should be noted that this is not accounting all factors. Negative emissions could also impact biodiversity and food security (Boysen et al., 2017; Smith et al., 2016) (depending on the choice of technology and uncertainties regarding efficiency and management; some amount of negative emissions can probably be generated with relatively little impacts (Fuss et al., 2018)).

An additional novel aspect of our research in the discussion of the role of negative emissions related to carbon budgets is that we take into account partially irreversible damages. Most, if not all, traditional Integrated Assessment Models (IAMs) assume that when temperature decreases, damages decrease accordingly (Howard & Sterner, 2017). However, some types of damages, such as disappearing glaciers and species extinction, are irreversible, and, therefore, will remain even when temperature declines. We propose a modelling framework including partially irreversible climate damages in an IAM setting.

4.2. Economic impact of avoiding net negative emissions

We analyse the economic impact of avoiding net negative emissions using a simple and transparent integrated assessment model similar to DICE (Nordhaus, 2014) (see Methods). Gross GDP is calculated in this model using a production function based on technological progress (Total Factor Productivity, TFP), capital and population. Both climate mitigation costs and damage costs resulting from climate change impacts are subtracted from the gross GDP. The resulting net GDP is divided in a fixed share to consumption and investments. Therefore, the mitigation and damage costs induce a direct loss of consumption and an indirect effect on economic growth by affecting investments. The model maximises the total discounted per capita utility, which is a concave function of per capita consumption, using Pure Rate of Time Preference (PRTP) values spanning the current literature range. The temperature is calculated as a linear function of cumulative emissions using the Transient Climate Response to Emissions (TCRE) relation (Dietz & Venmans, 2019). We calibrated all factors in the model based on the literature (see Methods). For mitigation costs, the mitigation potential as a function of costs is calibrated to the literature range in the IPCC scenario database for AR5 and SR1.5 (underlying a range of mitigation options). In a scenario where net-negative emissions are allowed, the yearly CO_2 emissions are limited to -20 $GtCO_2$/year representing the limits due to biophysical, technical, economic and sustainability constraints. In the literature a wide range of values for the contribution of net negative emissions can be found, ranging from zero to more than 40 $GtCO_2$/yr (Fuss et al., 2018; Hanssen et al., 2020), similar to the literature range for high overshoot scenarios in the IPCC SR1.5 database (5-30 $GtCO_2$/yr) (Huppmann, Daniel and Kriegler, Elmar and Krey, Volker and Riahi, Keywan and Rogelj, Joeri and Rose, Steven K. and Weyant, John and Bauer, Nico and Bertram, Christoph and Bosetti, Valentina and Calvin, Katherine and Doelman, Jonathan and Drouet, Laurent an, 2018; Masson-Delmotte et al., 2018).. Avoiding net-negative emissions sets this limit to 0 $GtCO_2$/year. Unless stated otherwise, the end-of-century carbon budget is set to 600 $GtCO_2$, in line with a 1.5°C target (Masson-Delmotte et al., 2018) (median climate temperature estimate). Finally, for damage costs, we use a stylised function that can be scaled (using a damage coefficient) to mimic the entire range from the DICE damage function (Nordhaus, 2014) to the long-run damage function from Burke et al (Burke et al., 2015), with as default medium damage estimate, the meta-model damage estimate from Howard et al (Howard & Sterner, 2017). For baseline assumptions, we use the SSP2 scenario (covering medium estimates for GDP, population and emission growth, see Methods).

The economically optimal emission paths and associated macroeconomic costs of a scenario with and without net negative emissions are shown in Figure 1. These results are created using a medium mitigation cost level, medium damage function (i.e. Howard Total, see Methods), medium TCRE and the three pure rate of time preferences spanning the current literature range: 0.1%/year, as used in the Stern review (Hof et al., 2008), 1.5%/year, as used in DICE-2007 and following versions (Nordhaus, 2008), and 3%/year, as used in the original DICE model (Nordhaus, 1992b).

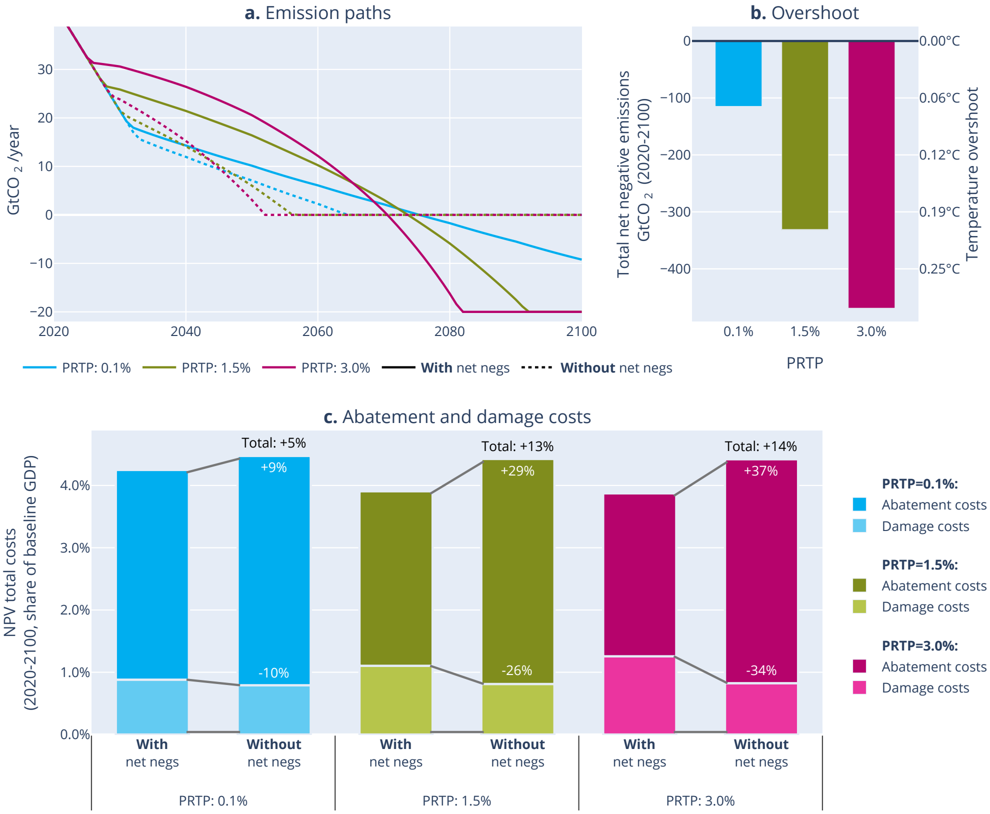

Figure 1. Difference in emission paths (a, b) and costs (c) between a scenario with and without net negative emissions. *These results are calculated for medium mitigation cost, medium TCRE and medium damage function (Howard Total) settings. The net present values (NPV) of the damage and mitigation costs are calculated with a fixed discount rate of 4%/year, regardless of the pure rate of time preference (PRTP) used.*

In a scenario where net negative emissions are avoided, strong emission reductions need to occur in the first half of the century to stay within the carbon budget (Figure 1a; dotted versus solid lines). In the scenarios that allow for net negative emissions, some mitigation effort is delayed to the second half of the century, reaching net zero around 2075 instead of 2050. While the net negative emissions have a higher marginal cost, the fact that they occur later in combination with discounting makes their use economically attractive. This also means that a lower PRTP significantly reduces the amount of net negative emissions, from 469 $GtCO_2$ with a 3% PRTP to 115 $GtCO_2$ for 0.1% PRTP (Figure 1b; see also Figure 1a for time profile). This corresponds to a temperature overshoot of respectively 0.29°C and 0.07°C (similar results were found in previous studies (Emmerling et al., 2019)).

Avoiding net negative emissions leads to a reduction in damage costs varying from 10 to 34%, caused by a combination of avoiding overshoot and earlier mitigation effort (Figure 1c). Simultaneously, the mitigation costs increase between 9% for low discount rates and 37% for the highest discount rate assumed, leading to an increase in total costs (sum of damage and mitigation costs) of 5% to 14%. Both damage and mitigation costs are calculated using their Net Present Value (2020-2100) with a fixed 4% social discount rate, regardless of their PRTP value (see Methods).

In other words, in all cases, allowing for some negative emissions is for medium parameters settings for mitigation and damage costs, from an economic perspective, attractive (even if damages are accounted for). The level of this preference, however, depends on the discount rate.

An important aspect to consider is the timing of mitigation effort and incurred damages. In Figure 2, we show the abatement costs and damage costs over time. For medium parameter values, the peak of total costs (abatement plus damage costs) occurs towards the end of the century when allowing net negative emissions (2%, 5% and 8% of GDP for respectively 2030, 2060 and 2090). When net negative emissions are not allowed, the peak in total costs is much earlier, albeit slightly lower (4%, 6.5% and 4% of GDP for 2030, 2060 and 2090). Once the minimum emission level is attained, the relative mitigation costs decrease due to technological learning and the increasing baseline GDP of SSP2. The corresponding global carbon prices are shown in Supplementary Figure 7 and reach a maximum of 800-1000 USD/tCO_2 when avoiding net negative emissions and 810-1250 USD/tCO_2 when net negative emissions are allowed (as a comparison, the European Trading System carbon prices are around 40 €/tCO_2 in 2021).

Besides discounting, the assumed level of climate damages plays an important role in determining the economic attractiveness of net negative emissions as well. In Figure 2, we perform a sensitivity analysis on the damage function (specifically, the damage coefficient, see Methods). We use a low damage function (DICE, giving 2% GDP loss at 3°C warming),

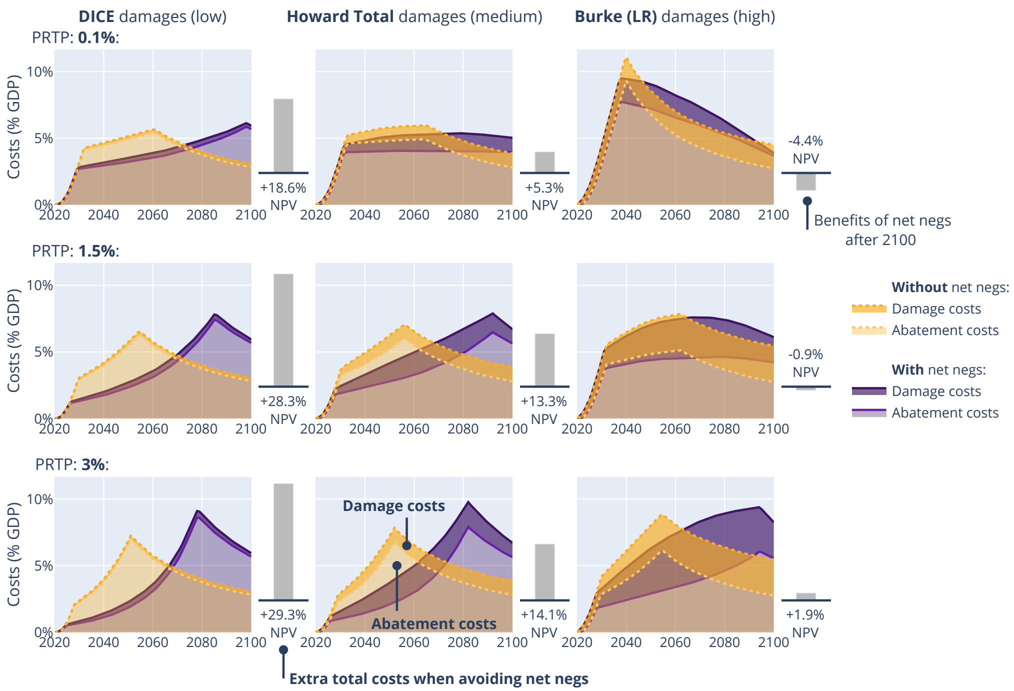

Figure 2. Timing of abatement costs (light shade) and damage costs (dark shade) *for scenarios without (yellow) and with (purple) net negative emissions, as a percentage of GDP. The columns represent three levels of damage functions (low, medium and high), the rows represent three values of the pure rate of time preference (PRTP). The grey bars give relative change in net present value (NPV, 2020-2100) of total costs (abatement plus damage costs) when avoiding net negative emissions. The NPVs are calculated using a fixed social discount rate of 4%/year. When this change is negative, the economic benefits of allowing net negative emissions only happen after 2100.*

a medium one (Howard Total, 9% GDP loss at 3°C) and a high damage function (Burke LR, 22% GDP loss at 3°C). For the low damage function, the extra mitigation effort early in the century when avoiding net negative emissions leads to much higher total costs (19% to 29% increase in NPV of total costs). However, when the damage function is high, the early emission reduction leads to significantly lower damages, making the total cost difference smaller.

For the Burke damage function with low PRTP, the total costs are minimal when no net negative emissions are used. For such a high damage function, the economically optimal emission path is to reduce as much as possible at any point in time. Allowing net negative emissions allows for deeper reductions throughout the century, with corresponding higher mitigation costs but lower damages. The effect of these lower damages increases further after

2100. Since in Figure 2, we report the NPV from 2020 to 2100, but we optimise discounted utility until 2150, it is possible to obtain higher total costs until 2100 in a scenario with no net negative emissions than in a scenario with negative emissions.

The damage function (specifically, the damage coefficient, see Methods) and the mitigation cost level have an equally strong influence on the difference in total costs. We perform a sensitivity analysis on these three factors: PRTP, damage coefficient and mitigation cost level. For each combination of parameter values, we run a scenario with and one without net negative emissions and calculate the increase in total costs between the two (Supplementary Figure 11). The extra costs, from low mitigation costs to high mitigation costs, range from +0% to +24% (with medium values for the other parameters). For damage cost uncertainty, the extra costs range from +0% to +28% from low damages (DICE) to high damages (Burke), again with all other values medium.

Higher mitigation costs always lead to higher additional costs of avoiding negative emissions, as depicted by the differences between the panels in Supplementary Figure 11. The impact of damage cost uncertainty is similar to the impact of mitigation cost uncertainty: the higher the damage coefficient, the earlier the mitigation effort occurs to avoid high climate damages later in the century. Early abatement action leads to a decrease in total net negative emissions (Supplementary Figure8). In fact, the emission paths, and associated cost differences between allowing and avoiding net negative emissions of a scenario with low mitigation cost and medium damage function are very similar to a scenario with medium mitigation costs and high damages. The total costs, relative to GDP, are, of course, significantly higher in the latter scenarios.

Interesting interactions between these parameters can be observed. First, the influence of damage costs uncertainty on timing increases with lower mitigation costs, simply because the relative importance of damages in total costs increases. As a result, in the case of low mitigation costs and high damages, avoiding negative emissions hardly leads to additional total costs. The additional costs even become slightly negative, as was already shown for high damages and low discounting in Figure 2, which is possible as utility until 2150 instead of total costs until 2100 is optimised. It can also be noted that the impact of higher damage estimates becomes non-linear for the combination of low mitigation cost levels and low PRTP: in that case, the optimal emission path stays significantly below the set carbon budget (see Supplementary Figure 9). For this set of parameters, a higher damage coefficient leads to more net negative emissions to keep climate-related damages at a minimum.

The costs differences become significantly lower when using a less stringent carbon budget. When using a carbon budget reaching 2°C instead of 1.5°C, avoiding net negative emissions only leads to extra costs when mitigation costs are high, or damages low (Supplementary Figure 18).

The effect of using the low or high instead of the median value of the TCRE is only significant for high damage coefficients. A high TCRE accentuates the effect of climate impacts resulting in more negative emissions if allowed in the scenario (Supplementary Figure 8).

4.3. Partially irreversible climate damages

We have shown that if climate damages are reversible, it is in most cases economically optimal to allow some net negative emissions (and thus exceed the peak budget). However, not all damages might be fully reversible. While climate impacts like reduced yields, health impacts and extra energy consumption for air conditioning are likely to be reversible, disappearing glaciers, species extinction and biodiversity loss are clearly irreversible processes. For other factors, it is more uncertain: while sea-level rise could be considered an irreversible process due to ice melting, the slow timescale at which it occurs also makes it relatively insensitive to a limited period of temperature overshoot.

Here, we investigate the consequences of assuming that a share of the damages is irreversible. The implementation details are discussed in SI 1.1. However, to properly assess the impact of (ir)reversibility of climate impacts, the carbon budget constraint must be changed. The reason is that the damages (and thus the optimal pathways) do not depend anymore on the cumulative net emissions. In fact, enforcing a carbon budget goal could be so restrictive that the model shows negative emissions even without any reversibility, which does not make any economic sense. We therefore translate the carbon budget to a maximum damage target for 2100 (see Methods). Such a maximum damage target inevitably depends on the assumed

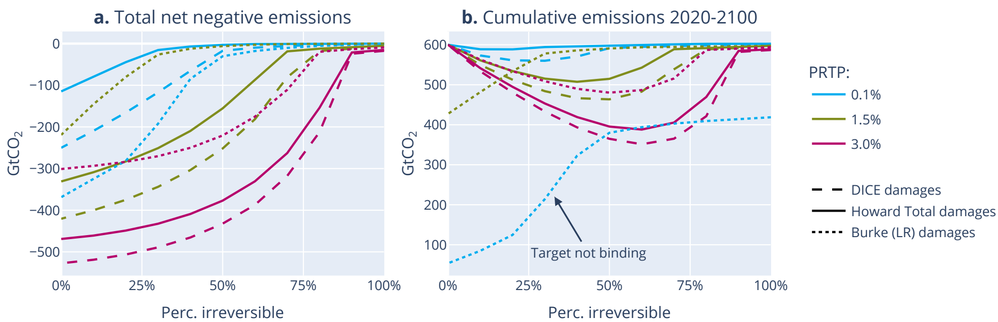

Figure 3. Effect of assuming partially irreversible damages. *(a) the total amount of net negative emissions. (b): the cumulative emissions from 2020 to 2100, as a function of the percentage of irreversible damages. The colours represent the pure rate of time preference (PRTP), while the dash/dot respectively the low and high damage function. All scenarios are run with a maximum damage target for 2100 derived from a carbon budget of 600 GtCO2.*

damage function. The 600 $GtCO_2$ carbon budget translates to maximum damage costs in 2100 of respectively 0.25%, 1% and 2.7% of GDP for the DICE, Howard Total and Burke (LR) damage functions.

Figure 3a shows that the amount of economically optimal net negative emissions is strongly dependent on the percentage of irreversible damages. For low discounting, net negative emissions are almost entirely unattractive when 30% of damages are irreversible. This happens around 70% of irreversibility for medium discounting – but the use of net negative emissions is already a factor 2 lower if 50% of damages are irreversible. For high discounting, the irreversibility of damages only becomes significant beyond a share of 50%.

As a consequence of the irreversibility of damages, net negative emissions need to be compensated by extra mitigation effort to reach the maximum damage target (Figure 3b). When damages are (almost) fully reversible, the cumulative emissions are close to the original carbon budget from which the damage target was derived, even when using a high amount of net negative emissions (left part of Fig. 3b). When damages are partially irreversible, it becomes economically attractive to have some overshoot (155 $GtCO_2$ for medium assumptions), even at the cost of extra mitigation effort (85 $GtCO_2$ for medium assumptions, middle part of Fig. 3b). When damages are even more irreversible, net negative emissions become less attractive, leading again to cumulative emissions close to the original carbon budget (right part of Fig. 3b).

An exception for this is the combination of high damage function and low discounting (dotted blue line in Fig. 3b): the damage target constraint is not economically optimal anymore, resulting in lower cumulative emissions than prescribed by the maximum damage target.

4.4. Discussion

Time evolution of GDP

Avoiding an emission overshoot requires earlier mitigation effort, leading to increased total discounted costs (Fig. 1c). This influences the GDP growth path. As shown in Supplementary Figure 6, the mitigation costs in 2030 are twice as high when avoiding the overshoot, while the damages are still the same with and without net negative emissions. By 2070, the total costs (mitigation and damage costs) reach the same level in both scenarios. At the end of the century, the absolute GDP level of the scenario avoiding overshoot is significantly higher since the mitigation costs for the negative emissions start to increase after 2070. However, since we optimise on cumulative discounted utility and not on final GDP, the overshoot scenario is still economically favourable. Moreover, since the net negative emission costs are assumed to be phased out after 2100 to keep the same carbon budget, the GDP paths of both scenarios will gradually converge.

Non-monetary aspects

In this paper, we only consider the macroeconomic effects of different emission paths: the increased monetary cost of climate policy (abatement costs) and the reduction of climate change damage due to earlier abatement effort. However, as mentioned in the introduction, this does not include the extra pressure on ecosystems and biodiversity due to the increased use of land-use related negative emission options such as BECCS and afforestation (Boysen et al., 2017; Fuss et al., 2018; Smith et al., 2016), the massive logistical and political bottlenecks associated with upscaling negative emission technology (Field & Mach, 2017; Shue, 2017), or the risks of non-performance at any point in the future. While it seems that some amount of negative emissions can be achieved without too many negative side effects (Fuss et al., 2018) (or that some technologies, like afforestation and soil carbon management, could even have some co-benefits), the negative other consequences should still be weighed against the economic results presented in this paper.

Reversibility of climate damages

We have shown that the amount of net negative emissions is strongly dependent on the extent to which climate damages are reversible. However, "reversibility" in climate change is a broad concept. In the literature on reversibility and climate change, three distinct effects are described, mostly independently of each other. First, climate reversibility, describing how temperature behaves under decreasing concentrations of atmospheric CO_2. Second, the impact reversibility, which analyses how, and if climate damages decrease when temperature decreases. Third, the economic persistence, which treats the long term economic effects of a shock due to climate change.

Regarding the first topic of climate reversibility, our model assumes that temperature is directly proportional to cumulative emissions. Previous research has shown (Frölicher & Joos, 2010; Wu et al., 2015; Zickfeld et al., 2016) that the assumption of fixed temperature/concentration relation might not fully hold: under decreasing atmospheric CO_2 concentrations, temperature decreases at a slower rate than when concentrations are rising. The impact is relatively small for a relatively small overshoot and the discrepancy with our modelling method, which focuses on the reversibility of damages is expected to be small.

The second concept, impact reversibility, is what we consider in this paper as irreversible climate damages. As already described, due to irreversible processes in biodiversity loss, melting glaciers and socio-economic tipping points, not all damages will decrease when temperature decreases.

The third concept is economic persistency. Empirical economic research has shown that climate change does not only induce direct monetary losses (like destroyed real estate after a flood) but also impacts economic growth (Burke et al., 2015; Estrada et al., 2015; Piontek et al., 2019). The latter has a much longer-term effect. This paper considers this indirectly by using the Burke et al. (Burke et al., 2015) damage function at the high end of our sensitivity range on climate damages. While we have translated the growth effects of Burke et al. to a direct temperature-GDP loss relation (therefore not affecting growth rate), the underlying calibration still uses growth impacts (see Methods).

While the second and third concepts (impact reversibility and economic persistence) might be related, the exact relationship is still unclear. In fact, economic persistence also happens when temperatures are increasing, whereas impact reversibility is only relevant for decreasing temperatures.

Comparison to other literature

The increased mitigation costs when avoiding net negative emissions have already been assessed by Hilaire et al. (Hilaire et al., 2019) They analysed recent IAM mitigation scenarios reaching 1.5°C and 2°C with varying levels of negative emissions. For the 1.5°C target, mitigation costs go from 2.26% of GDP for unconstrained BECCS to 4.1% of GDP with limited BECCS (both cost values are NPV 2010-2100, 5%/year), an increase of over 80%. In this study, we find an increase in mitigation costs of 9% to 37% for medium parameter values. This large discrepancy comes from two reasons. First, we calculate the NPV using a smaller discount rate of 4% instead of 5%, giving more weight to future generations (if we used 5%, the cost increase would be up to 53% for medium values). Second, and most importantly, we take damages into account when calculating the economically optimal emission trajectory, whereas most traditional IAMs under carbon budget calculate the cost-effective path, ignoring climate damages.

4.5. Conclusions and implications

Our results suggest that economically, some form of overshoot is attractive, even when considering the extra damages in the optimisation process. The choice to avoid negative emissions, and thereby interpreting the Paris Agreement target as a "no overshoot" target will lead to a sum of abatement costs and damage costs that is around 13% higher than without the restriction when using a pure rate of time preference of 1.5% and the medium damage function. Still, the cost differences are much smaller if mitigation costs are assumed to be relatively small (compared to the literature median), damages high, or when a low discount rate is used. Moreover, assuming that climate damages are not fully reversible significantly reduces the attractiveness of net negative emissions. Assuming that 50% of damages are irreversible leads to 50% lower total net negative emissions, since extra mitigation effort is required to reach the same maximum damage target when using net negative emissions. Under a wide range of assumptions on damages, mitigation costs, time preference, reversibility of damages, we find that the attractiveness of negative emissions is much lower than often shown in scenarios based on optimisation of mitigation costs only.

4.6. Methods

In this paper, we use a simple and transparent integrated assessment model described in detail in the SI. The model is similar to DICE (Nordhaus, 2014). Gross GDP is calculated using a production function based on technological progress (Total Factor Productivity, TFP), capital and population. The mitigation costs and the damage costs resulting from climate change impacts are subtracted from the gross GDP. The net GDP is divided in a fixed part (21%) of investments and the rest to consumption. The model maximises the total discounted per capita utility, which is a concave increasing function of per capita consumption. Greenhouse gas emissions are calculated by multiplying economic activity with an emission factor.

Each timestep, the emissions are added to the cumulative emissions. The cumulative CO_2 causes a change in global mean temperature, modelled through the instantaneous and linear TCRE (transient climate response to emissions) relation (Dietz & Venmans, 2019). This relation includes a linear relation between non-CO_2 and CO_2 emissions. The global mean temperature, in turn, determines the damage costs. In response, the model can determine to mitigate emissions. The mitigation level (or equivalently the carbon price) over time is determined by maximising the Net Present Value (NPV) of utility. The mitigation costs are subtracted from investments and consumption.

4.6.1. Calibration

The parameters are as much as possible calibrated against existing literature. Population, baseline emission intensity and TFP are exogenous and calibrated to match the growth rates of the Shared Socio-economic Pathways (SSPs) (Riahi et al., 2017c). We use the SSP2 ("Middle of the Road") scenario which has medium assumptions about population growth, emissions, GDP, technological growth and lifestyle. For details, see Riahi et al. (Riahi et al., 2017b) and for the exact implementation in our model see SI 1.2.

Emission reductions are quantified through a quadratic Marginal Abatement Cost (MAC) curve. The area under the MAC gives the mitigation costs. The resulting mitigation costs are calibrated using the consumption loss range of the 5th Assessment Report of the IPCC (IPCC, 2014). To consider the wide range in mitigation costs, we perform a quantile regression on the AR5 data points to the 5th, 50th and 95th percentiles to represent the low, medium and high end of the mitigation cost range. The 5th percentile leads to mitigation costs 2.5 times smaller than the median costs, the 95th percentile 2.5 times larger.

The damage function is defined as a quadratic function of global mean temperature T:

$$D(T) = c \cdot T^2,$$

where $D(T)$ is the fraction of GDP loss due to climate impacts. The damage coefficient c is calibrated to capture the full literature range.

At the low end, we choose the DICE-2013R damage function (Nordhaus, 2014) with $c = 0.00267$. The medium estimate is based on the results from a meta-analysis of literature damage functions by Howard et al (Howard & Sterner, 2017), with a damage coefficient of $c = 0.01004$. The high end of the range is parametrised by the long-run empirical damage from Burke, Hsiang and Miguel (Burke et al., 2015). While their damage estimates are quantified as impacts on growth rates and not directly on GDP, we use the iterative strategy from recent literature (Glanemann et al., 2020) to create a damage function usable by IAMs like our model. The idea of this method is to calculate which direct GDP losses would result in the same GDP path as when Burke's growth impacts are used. Iteratively, a damage curve (as function of temperature change) is created giving the same damages as the growth impact definition (Van der Wijst, Hof, van Vuuren, 2021). A quadratic function is then fitted to the resulting approximation ($R^2 = 0.99$), leading to $c = 0.02835$, about 10 times higher than the DICE damage function.

The utility discount rate, called throughout this paper the Pure Rate of Time Preference (PRTP), is chosen to be 0.1%/year, as used in the Stern review (Hof et al., 2008), 1.5%/year and 3%/year, as used in DICE-1999, DICE-2007 and following versions (Nordhaus, 2008; Nordhaus & Boyer, 2000). The elasticity of marginal utility is 1.001. The combination of PRTP and elasticity of marginal utility are in line with the expert elicitation by Drupp et al (Drupp et al., 2018).

The minimum yearly emission level in the scenarios without net negative emissions, is, by definition, set at 0 $GtCO_2$. The potential for net negative emissions is limited by biophysical, technical, economic and sustainability constraints. In the literature a wide range of values for the contribution of net negative emissions can be found, ranging from zero to more than 40 $GtCO_2$/yr. For instance, Fuss et al. (Fuss et al., 2018) estimated a maximum sustainable supply of about 5 $GtCO_2$/yr for individual CDR options in 2050 – but the combination of these options could be higher, while Hanssen et al. (Hanssen et al., 2020) showed a maximum potential of 40 $GtCO_2$/yr in 2100. The literature range for 1.5°C scenarios in the IPCC Special Report on 1.5°C is around 5 $GtCO_2$ to 30 $GtCO_2$/yr for overshoot scenarios. Here, we limit the contribution of net negative emissions to a maximum of 20 $GtCO_2$/yr. Moreover, to account for technological and political inertia, we assume that the emissions cannot be mitigated faster than 2.2$GtCO_2$ per year (based on the maximum reduction speed of the IPCC 1.5°C database (Huppmann, Daniel and Kriegler, Elmar and Krey, Volker and Riahi, Keywan and Rogelj, Joeri and Rose, Steven K. and Weyant, John and Bauer, Nico and Bertram, Christoph and Bosetti, Valentina and Calvin, Katherine and Doelman, Jonathan and Drouet, Laurent an, 2018)) for each scenario. Finally, from the year 2100 onwards, the cumulative emissions from 2020 cannot exceed a carbon budget. Unless stated otherwise, the carbon budget is set to 600 $GtCO_2$, in line with a 1.5°C target (Masson-Delmotte et al., 2018).

Finally, the Transient Climate Response to CO_2 Emissions (TCRE) determines the increase in global mean temperature per unit of extra CO_2 emissions (Dietz & Venmans, 2019). Using the method from van Vuuren (2020) (Van Vuuren et al., 2020), the TCRE used here is calibrated to key results from the Working Group I from the IPCC AR5 report (IPCC, 2013). In this paper, three values are considered, corresponding to the uncertainty range's 5th, 50th and 95th percentile. Unless mentioned differently, we use the median value for the TCRE, equal to 0.62°C per 1000 $GtCO_2$.

The percentage of climate damages which is irreversible has, to the best of our knowledge, not been fully estimated in current literature. While several studies have shown that impacts like decreased precipitation (Solomon et al., 2009) and sea level rise (Hinkel et al., 2014; Nauels et al., 2019) can continue to increase after atmospheric CO_2 concentrations have stabilised, there is notoriously less literature quantifying how these impacts behave when emissions become net negative. For this reason, we cover the full range from 0% (fully reversible) to 100% (fully irreversible), even though neither of these extremes is realistic.

4.6.2. Cost comparison

The abatement and damage costs in this paper are presented as Net Present Value (NPV) relative to baseline GDP:

$$\text{relative costs} = \frac{\text{NPV(abat. costs)}}{\text{NPV(baseline GDP)}}$$

and similar for the damage costs, where NPV is calculated as discounted sum until timestep T:

$$\text{NPV}(x) = \sum_{t=0}^{T} e^{-rt}\big(x(t)\big)$$

A fixed social discount rate of 4%/year is used, in line with our medium PRTP value and elasticity of marginal utility (see SI 1.2). In order to compare the macroeconomic costs of a scenario with and without net negative emissions, the ratio of their net present value GDP losses are calculated:

$$\text{cost diff.} = \frac{\text{relative costs}_{\text{with net negs}}}{\text{relative costs}_{\text{without}}} - 1$$

Supplementary Information

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Comparing mitigation, adaptation and residual damage costs under different socio-economic and climate scenarios

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Under review

Future socio-economic development plays a crucial role in both climate policy and the impacts of climate change. In this study, we for the first time systematically compare the costs of mitigation, adaptation, and residual damage for different socio-economic and climate scenarios known as the Shared Socio-economic Pathways (SSPs). For this, we combine recent damage estimates with adaptation costs and introduce differences in the effectiveness of adaptation based on the SSP projection. The results can be presented in terms of SSP/RCP matrix, with optimal climate outcomes as a function of SSP. The results can also be used to identify critical factors determining the optimal temperature, including socio-economic development, technology development and limits to mitigation and adaptation. The socio-economic limits to adaptation lead to damage costs that are 15% to 60% higher than if optimal adaptation had been possible. Overall, this study demonstrates that the socio-economic developments assumed in the SSP, including inequality reduction and institutional strength, can be equally important for the optimal outcome as the factors typically studied such as discount rate.

5.1. Introduction

Optimal climate policy aims to strike a balance between mitigation efforts, adaptation to the impacts of climate change, and accepting some residual impacts. One crucial element to consider is that these factors are uncertain and depend, among others, on socio-economic developments. In 2014, the SSP-RCP framework was suggested to help assess these factors systematically in relation to socio-economic development. The SSPs (Riahi et al., 2017a) (Shared Socio-economic Pathways) define five socio-economic storylines based on challenges to mitigation and adaptation, while the RCPs (Van Vuuren et al., 2011) (Representative Concentration Pathways) reflect emission pathways resulting in different climate outcomes, quantified through the radiative forcing reached in each pathway. The goal of the SSP-RCP framework was to assess different levels of mitigation and adaptation simultaneously. Interestingly, such systematic research based on the SSP-RCP matrix still does not exist. While the scenarios were extensively used in mitigation and impact research, an integrated analysis looking at both (challenges to) mitigation and adaptation is missing (O'Neill et al., 2020; van Maanen et al., 2023). In this paper, we present to our knowledge for the first time, the first systematic analysis of the SSP-RCP matrix combinations, looking simultaneously at mitigation costs, residual damages, and adaptation.

In model-based scenario analysis, challenges to mitigation have been translated into parameters that influence the mitigation potential including so-called Shared Policy Assumptions (SPAs) (Kriegler et al., 2014). Despite the fact that the (in)effectiveness of adaptation is similarly important given the direct impact on damages inflicted by climate change. Very few cost-benefit Integrated Assessment Models (IAM) (but also impact studies) explicitly pay attention to adaptation (van Maanen et al., 2023). Exceptions include AD-RICE (De Bruin, Dellink, Tol, 2009; Hof et al., 2009) and AD-WITCH (Agrawala et al., 2011; Bosello et al., 2010) and some studies that only implicitly included adaptation without explicit modelling (Glanemann et al., 2020; Hof et al., 2008; Van Der Wijst et al., 2023; Van der Wijst, Hof, van Vuuren, 2021). Most studies including adaptation assume optimal adaptation, which is highly unlikely (Juhola et al., 2016; Magnan et al., 2016; Patt et al., 2010; Schipper, 2020). The SSPs explicitly include storylines with high challenges to adaptation, but Shared Policy Assumptions (SPAs) (Kriegler et al., 2014) quantifying adaptation challenges do not exist yet. We therefore also introduce adaptation costs and SSP-based assumptions on the effectiveness to address this issue and create cost matrices of mitigation costs, adaptation costs and residual damages and compare them to find economically cost-optimal pathways for each SSP.

It is necessary to estimate to which degree societies can adapt to climate change to project adaptation costs and residual damages. Stronger adaptation lowers residual damages but increases adaptation costs. Literature on the costs of adaptation on a global scale is sparse (van Maanen et al., 2023). Here, we use the estimates from AD-RICE, developed by de Bruin et al (De Bruin, Dellink, Agrawala, 2009; Hof et al., 2009). Previous research (Andrijevic et al., 2020) has shown that the level of adaptation is not only the result of an optimisation process balancing the adaptation costs and residual damages, but also depends on the level at which countries are able to implement adaptation policies. In this paper, we incorporate this by using a regional, time-dependent reduction factor which lowers the actual adaptation level below the optimal level. This factor is based on a time-dependent, SSP-specific adaptation readiness index extrapolated from the ND-GAIN data by Andrijevic et al (Andrijevic et al., 2020). This factor takes into account the different governance levels for each SSP and country and is therefore a useful proxy for the different challenges to adaptation of each SSP (van Maanen et al., 2023; Magnan et al., 2016).

In line with previous studies (Bosello et al., 2010; De Bruin, Dellink, Agrawala, 2009; De Bruin, Dellink, Tol, 2009), we calculate residual damages as a percentage of the gross damages – the damage costs without any adaptation – determined by the adaptation level. For damages, we use the recently published probabilistic COACCH damage functions (Van Der Wijst et al., 2023), which have been developed by aggregating the damages for a wide range of sectors (agriculture, forestry, fishery, energy demand and supply, labour supply, riverine floods, transportation and sea-level rise). An advantage of using these damage functions is that adaptation is explicitly modelled for sea-level rise. The other sectors, unfortunately, do not model adaptation explicitly. For these sectors, we select the damage function such that when optimal adaptation is assumed, the same level of damages, including adaptation costs, are reached as with the medium COACCH damage function (50th percentile) (Van Der Wijst et al., 2023) (see Methods), using a similar methodology as previous studies (De Bruin, Dellink, Agrawala, 2009; De Bruin, Dellink, Tol, 2009). Clearly, several damage categories are not included in these functions, including biodiversity losses and tipping points.

Our results show that the high damage costs (8-9% in RCP6.0) for high emission scenarios are much higher than the high mitigation costs for stringent climate targets (2-3% for RCP1.9). Socio-economic limits to adaptation lead to damage costs of 15% to 60% higher than if optimal adaptation had been possible. While, in current literature, most of the focus is given to the mitigation level, this study shows that socio-economic developments, like inequality reduction and institutional strength, can be equally important.

5.2. Results

We analyse the mitigation and adaptation costs and residual damages for each combination of SSPs (SSP1 through SSP5) and RCPs (RCP 1.9 through RCP 6.0), except for those combinations that are generally seen as infeasible (SSP1-6.0, SSP3-1.9 and 2.6, SSP4-1.9 and SSP5-1.9, see Methods). To accomplish this, we run a cost-effective scenario using the Integrated Assessment

Model MIMOSA (Van Der Wijst et al., 2023; Van der Wijst, Hof, van Vuuren, 2021), using the socio-economic assumptions of each SSP, while imposing a temperature target matching the radiative forcing of each RCP. For each of the resulting scenarios, we calculate the net-present value of the mitigation costs, the adaptation costs, and the residual damages and present them in matrix-form in Fig. 1a (mitigation costs), Fig. 1b (adaptation plus residual damages) and Fig. 1c (total costs, i.e. sum of mitigation, adaptation and residual damage costs). Finally, the total costs allow us to select the RCP with least total costs, for each SSP, and compare this with the cost-benefit run (CBA) without any temperature target or carbon budget imposed.

5.2.1. Mitigation costs

The mitigation costs naturally increase with the stringency of the climate target (Fig 1a). However, there are strong differences between the various SSPs: reaching RCP 2.6 costs 0.8% of GDP for SSP1, and up to 2.8% for SSP4. The differences between SSPs arise from several factors: (a) different baseline emissions, (b) different marginal abatement costs (due to preferences and technology development related to SSPs), (c) regionally differentiated carbon prices and (d) different GDP paths, including the impact on discounting (Table 1). Reaching RCP2.6 in SSP3 is not possible due to a combination of high baseline emissions and low mitigation potential. Indeed, as shown in Suppl. Fig. 2.4, baseline CO_2 emissions vary greatly between SSPs, with cumulative emissions from 2020 to 2100 of 3000, 4900 and 7100 $GtCO_2$ for respectively SSP1, SSP3 and SSP5.

Absolute mitigation costs are not only determined by the total amount of emissions to be reduced, but also by the marginal costs of reducing a unit of emissions. The end-of-century marginal abatement costs are projected to be 20-30% higher in SSP3 and SSP5 than in SSP2 due to the increased challenge for mitigation in the narrative, reflected in technology assumptions and the reduction potential. In MIMOSA, this is quantified by an SSP-dependent Marginal Abatement Cost (MAC) curve based on existing literature (see Methods). Conversely, SSP1 has about 40% lower marginal abatement costs in 2100 compared to SSP2. The challenges to mitigation, as described in the SPAs, also originate from a different timing of global cooperation for climate policy. In this study, we apply a welfare loss minimisation to determine regional mitigation contributions: costs incurred in poorer countries have a larger weight than those incurred in richer regions. This method leads to endogenously differentiated carbon prices (see Methods), which are the most differentiated in SSP3 and SSP4 and lowest in SSP1, reflecting the SPAs for mitigation (Kriegler et al., 2014). Due to the differentiated carbon prices, overall mitigation costs are 25-30% higher in SSP3 and SSP4 compared to a situation with global carbon prices where costs were minimised, instead of welfare loss (Suppl. Fig. 2.6). The combination of large amounts of emissions to be mitigated, and higher relative marginal abatement costs, leads to high absolute mitigation costs in SSP3 and SSP5, and low absolute mitigation costs in SSP1, with SSP2 and SSP4 in between (Fig. 1d).

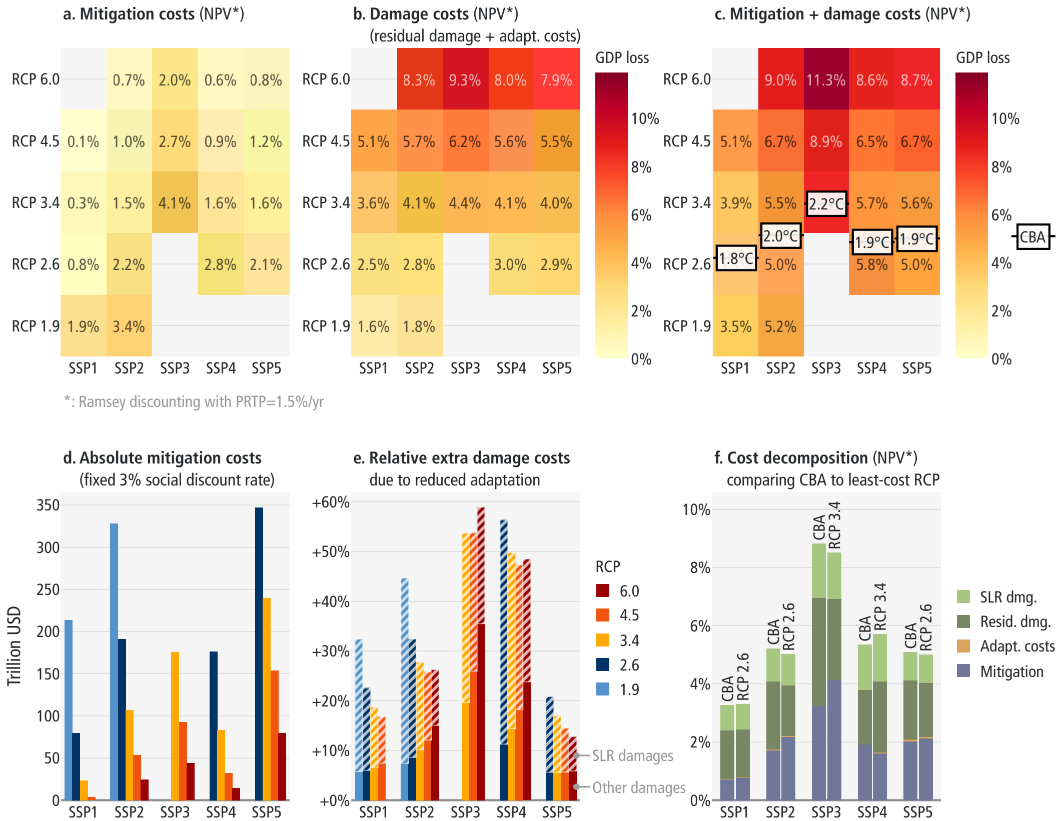


Figure 1. Cost matrices of mitigation costs (a), damage costs (sum of residual damages and adaptation costs, b) and the total costs (sum of mitigation and damage costs, c)*, calculated as net present value using Ramsey discounting, relative to the NPV of GDP. In panel c, the 2100 temperature of the corresponding cost-benefit scenario (CBA) is shown. The y-position of the CBA label corresponds to the translated radiative forcing level of the CBA run. For each SSP-RCP combination, the absolute mitigation costs (in trillion USD) are shown in panel d, as well as how much larger the damage costs are compared to a situation where fully optimal adaptation would have been assumed (panel e). In panel f, the total costs are decomposed into mitigation costs, adaptation costs, residual non-sea-level rise damages and residual sea-level rise damages, both for the least-cost RCP as well as the cost-benefit path. Note that in Fig. 1d, to facilitate comparison between SSPs, the absolute mitigation costs have been discounted using a fixed discount rate of 3%/year, to avoid the added SSP fingerprint when using Ramsey discounting, which is dependent on the GDP growth rate.*

The high absolute mitigation costs explain the very high relative mitigation costs of SSP3 in the mitigation cost matrix. The absolute mitigation costs are also high in SSP5, based on the high baseline emission and high marginal abatement costs (reflecting the high challenges to mitigation). However, in terms of costs per GDP the costs are lower in this baseline due to the very high baseline GDP path (Suppl. Fig. 2.5). Conversely, the low GDP path of SSP4 results in high relative mitigation costs.

Finally, since the costs are calculated as Net Present Value (NPV) using Ramsey discounting (see Methods), a high economic growth rate means a higher discount rate, amplifying the effect that high GDP results in relatively lower mitigation costs.

5.2.2. Damage costs

Our results show damages (residual damage and adaptation costs) of 7.9-9.3% of GDP (NPV) in RCP 6.0, while for RCP 2.6 they drop to 2.5-3.0%. This means that the highest damage costs are about three times as high as the mitigation costs in the most stringent climate policy RCPs. As with mitigation costs, there are significant differences in damage costs between the SSPs (Fig. 1b), even though the temperature targets and damage functions are harmonised. The differences arise mainly due to (a) different adaptation levels, (b) different GDP growth and, to a lesser extent, (c) different timing in mitigation across the different SSPs (Table 1).

The high challenges to adaptation in SSP3 and SSP4 lead to reduced adaptation levels, which in turn imply higher damage costs. For RCP4.5, the total damage costs (residual damages plus adaptation costs) are about 50% higher in SSP3 and SSP4 compared to a situation with optimal adaptation, while SSP1 and SSP5, with low challenges to adaptation, only have 15-20% extra damage costs due to sub-optimal adaptation (Fig. 1e). This highlights the need of higher adaptation readiness than is currently projected in most SSP narratives. Except for SSP3-RCP 6.0, more than half of these extra damage costs come from extra sea-level rise damages, since cheap adaptation options can strongly reduce sea-level rise damages (Schinko, Drouet, Vrontisi, Hof, Hinkel, Mochizuki, Bosetti, Fragkiadakis, van Vuuren, et al., 2020; Van Der Wijst et al., 2023). For low RCPs, this share becomes even larger, since sea-level rise in the first half of the century are much less dependent on the RCP than other damages, due to their high inertia (Schinko, Drouet, Vrontisi, Hof, Hinkel, Mochizuki, Bosetti, Fragkiadakis, van Vuuren, et al., 2020).

Besides differences in adaptation, the NPV of the damage costs vary across SSPs due to different GDP trajectories. Even though the damage costs themselves are calculated as percentage of GDP, when calculating the NPV, relative costs are first translated to absolute costs, giving a larger weight to the damages incurred when GDP is highest. Since for high RCPs, the largest damages happen at the end of the century, and beyond, the NPV will be slightly higher. However, using Ramsey discounting slightly attenuates this effect since a higher effective discount rate is used when the GDP per capita growth rate is high.

	SSP1	SSP2	SSP3	SSP4	SSP5	Increases or decreases the costs?	Shown in:
Mitigation costs:							
Baseline emissions	Low	Medium	High	Low	Very high	Increases	Suppl. Fig. 2.4
Marginal abatement costs	Low	Medium	Very high	Medium	High	Increases	Extended Fig. 1d
Reginonally differentiated carbon prices	Low	Medium	High	High	Medium	Increases	Suppl. Fig. 2.6
Absolute mitigation costs	Low	Medium	High	Medium	High		Fig. 1d
GDP path	High	High	Low	Low	Very high	Decreases	Suppl. Fig. 2.5
Mitigation costs (as % of GDP)	**Low**	**Medium**	**Very high**	**High**	**Medium**		Fig. 1a
Damage costs:							
Extra costs due to sub-optimal adaptation	Low	Medium	High	High	Low	Increases	Fig. 1e
GDP growth	Medium	Medium	Low	Low	High	Increases*	Suppl. Fig. 2.5
Timing of mitigation	Early	Medium	Medium	Early	Late	Decreases when earlier**	Suppl. Fig. 2.4
Damage costs (as % of GDP)	**Low**	**Medium**	**High**	**High**	**Medium**		Fig. 1b

* Using Ramsey discounting slightly attentuates this affect

** Only has a very small effect on NPV (≤0.2% of GDP)

Table 1. Overview describing the main drivers of variation of mitigation/damage costs between the SSPs, *given a common climate target. The last column gives the reference to the figure where the specific driver/result is shown.*

Finally, a small difference in damage costs between SSPs is due to a different timing of mitigation action (at most around 0.2% of NPV GDP). While the same temperature targets are met for a given RCP, SSP5, for example, delays mitigation action more towards the end of the century, therefore relying more on net negative emissions and having higher damage costs towards the end of the century (Suppl. Fig. 2.4).

5.2.3. Adaptation costs

The adaptation costs shown in Figure 1 are much lower than the mitigation and damage costs. First, estimates of adaptation costs show that at lower levels of climate change, adaptation can be effective at relatively low costs (Extended Fig. 1c). Second, the assumptions made on challenges to adaptation lead to lower adaptation levels (and thus lower adaptation costs, but higher residual damages). However, while the adaptation costs expressed as percentage of NPV GDP are small, the yearly costs are still substantial: 50-220 billion US$ in 2070 in SSP2, growing to over 1000 billion US$ in 2100. These are well in line with current literature estimates (Suppl. Fig. 2.7) (Chapagain et al., 2020; Hof et al., 2009) . Finally, it should be noted that these adaptation costs do not cover sea-level rise adaptation costs, since they are already included in the sea-level rise damages (see Methods).

5.2.4. Total costs

Comparing the sum of mitigation, adaptation and damage costs across RCPs provides insight into cost-optimal climate targets for a given SSP (Fig. 1c). However, these scenarios were only calculated for a discrete set of five RCPs. Moreover, the timing of the RCP pathways do not take damages incurred throughout the century into account. To calculate the cost-optimal pathways for each SSP more accurately, and following recent best practices of including damages when calculating the emission pathway (Piontek et al., 2021; Van der Wijst, Hof, van Vuuren, 2021), we perform a cost-benefit analysis (CBA) for each SSP. The cost-optimal temperature target range varies from 1.8 (SSP1) to 1.9-2.0 (SSP2, SSP4, SSP5) and 2.2°C (SSP3). It should be noted that the damage functions used do not account for all damages, like biodiversity loss, health impacts and tipping points nor do they include synergies such as air pollution and therefore underestimate the actual damages (Van Der Wijst et al., 2023). While it might seem counterintuitive that the SSPs have similar optimal temperatures, the combined effect of different adaptation levels and different socio-economic developments counteracts the different mitigation costs typically associated with the SSPs.

For each SSP, the cost decomposition of the respective least-cost RCP is shown in Fig. 1f, compared to the cost decomposition of the CBA path. The mitigation costs make up roughly half of the total costs, residual damages (non-sea-level rise) 35%, residual sea-level rise damages 15% and adaptation costs less than 1% of total costs.

5.3. Discussion

This paper shows that different socio-economic developments play a key role in the quantification of mitigation costs and damage costs. Mitigation costs, the mitigation potential, the adaptation level and residual damages differ strongly across SSPs. The differences can become even larger when not only considering emissions and costs, but also material flows, nature preservation and other sustainability principles. While mitigation costs strongly depend on baseline emissions and marginal abatement costs, damages mainly depend on the level of adaptation - given a certain emission pathway. While adaptation is a very cost-effective way of reducing residual damage costs, the potential is severely limited due to socio-economic constraints, especially in SSP3 and SSP4.

However, in the current literature, a wide range of systematic, global and comprehensive adaptation cost functions is lacking. In this paper we use the AD-RICE 2009 data. Although newer version of AD-RICE 2012 (De Bruin, 2014) and AD-WITCH (Agrawala et al., 2011; Bosello et al., 2013) also exist, the main difference is here that adaptation cost functions are split into two types of adaptation: stock and flow adaptation, corresponding to respectively a buildup of indirect adaptation capital and spending on reactive, direct adaptation. For this paper, the distinction between the two types of adaptation costs is irrelevant, and only leads to numerically more complex simulations. Since the newer versions of adaptation cost functions are calibrated to yield the same total costs as the original AD-RICE 2009 version, these were used here.

This study assumes that the adaptation level is reduced from the optimal level according to the adaptation capacity of each region, year, and SSP. While the ND-GAIN index uses a variety of socio-economic indicators to model adaptation capacity, the actual implementation of adaptation might be dependent on other aspects as well, like political factors and local risk perceptions. Moreover, the challenges to adaptation are now modelled by a direct linear reduction of the adaptation level. Besides non-linear responses, another option would be a more endogenous approach, by increasing the adaptation costs in regions and SSPs with higher adaptation challenges which could be subject of future work if underlying data would become available.

Another, yet related, limitation is the lack of systematic damage estimates as function of adaptation. While there are several types of damage functions available in recent literature (Burke et al., 2015; Howard & Sterner, 2017; Nordhaus, 2014), none explicitly treat adaptation in a comprehensive way, at least not for all sectors (as an example, the COACCH damage functions only have explicit adaptation for sea-level rise). While using the 95th percentile (high end) of the COACCH damage function as gross damages leads to a medium residual damage level when using optimal adaptation, a better, more explicit representation of gross damages with corresponding adaptation cost function would be necessary to improve the estimates of the damage costs. Moreover, the COACCH damage functions are incomplete: they do not account for biodiversity losses, health impacts and tipping points. Expanding the research on comprehensive gross damage functions would also allow for a more consistent uncertainty analysis of the cost matrices in this paper.

The mitigation costs in this study seem higher than the mitigation costs presented in the original SSP paper (Riahi et al., Figure S2 (Riahi et al., 2017a)), but the difference is mainly attributable to a different discount rate. When recalculating the cost matrices from this study with a fixed social discount rate of 5%/year, the costs become very similar: all mitigation cost numbers are well within the range of Riahi et al. From an implementation point of view, the challenges to mitigation are implemented by having a SSP- and time-specific MAC curve, giving higher mitigation costs for SSP3 and SSP5 than SSP1, SSP2 and SSP4. Moreover, higher baseline emissions make mitigation even more challenging in SSP3 and SSP5. The Shared Policy Assumptions (SPAs) (Kriegler et al., 2014) define, for each SSP, a corresponding climate policy fragmentation phase. For SSP1 and SSP4, full regional collaboration is implemented after 2020, whereas this only happens in 2040 for SSP2 and SSP5 and more differentiated carbon prices for SSP3. MIMOSA also introduced fragmentated carbon prices but based on maximizing discounted utility taking inequality aversion into account (see Methods) (Suppl. Fig. 2.6). Rich regions take on a higher burden of the mitigation, favoring lower carbon prices in developing regions. Due to the higher inequality in SSP3, the resulting carbon prices are also more differentiated, matching the SPA storyline. For SSP1, SSP2 and SSP5 the level of differentiation in carbon price also matches the corresponding SPA storyline. On the other hand, due to the high inequality in SSP4, the carbon prices are also more differentiated, which does not match the quick global collaboration of the SPA of SSP4. However, since in the SSP story line, most of the mitigation happens in richer, developed countries, the overall effect of differentiated carbon prices is attenuated as these richer countries have a similar carbon price.

This analysis highlights the importance of systematically comparing mitigation costs to damages. The damage costs for high RCPs are much higher than the mitigation costs for low RCPs, giving economic validation to more stringent mitigation targets. The damage costs can be strongly reduced by a higher adaptation readiness. While the corresponding adaptation costs would increase, the total residual damages plus adaptation costs would be reduced by 13 to 37%, if the optimal adaptation level could be achieved. However, more research on adaptation is necessary to obtain a better estimate of this effect. Finally, the socio-economic developments (through, for example, different SSPs) are key in determining both the mitigation costs and the damage costs. In the climate policy debate, while most of the focus is given to the mitigation level, this study shows that socio-economic developments, like inequality reduction and institutional strength, can be equally important.

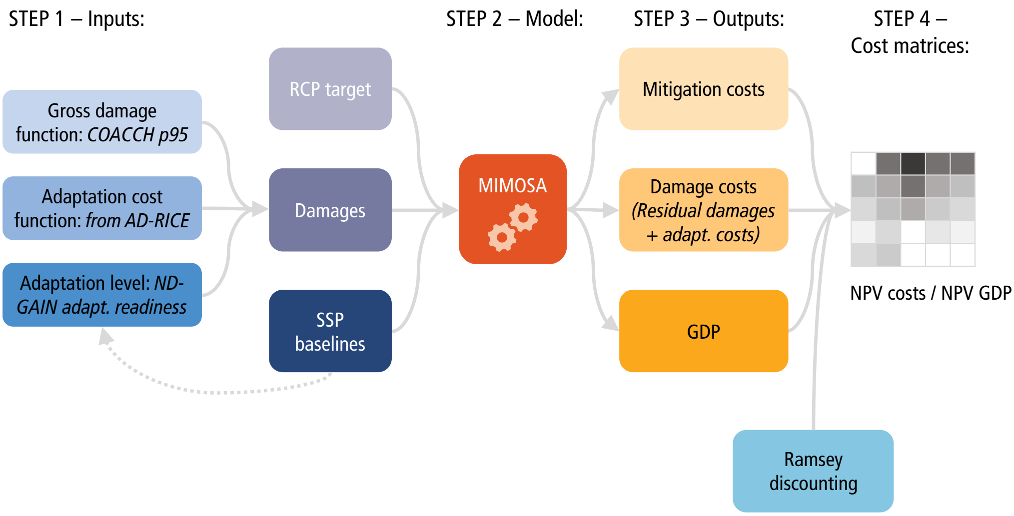


Figure 2. Overview of the methodology of creating the cost matrices. *The most important inputs to the MIMOSA model are the RCP target, the gross damage functions, adaptation cost functions and adaptation levels per SSP, as well as the SSP-specific data (baseline emissions, GDP path and SSP-dependent MAC calibration factor).*

5.4. Methods

A schematic overview of the methodology used to calculate the cost matrices is shown in Fig. 2.

5.4.1. The MIMOSA model

All model runs are performed using the reduced-form Integrated Assessment Model MIMOSA (Van Der Wijst et al., 2023; Van der Wijst, Hof, van Vuuren, 2021). It is a relatively simple, open source, Cost-Benefit IAM covering relevant technological and socio-economic dynamics, for 26 regions covering the whole world.

The economic module of MIMOSA consists of a Cobb-Douglas production function, where the Total Factor Productivity is calibrated using the baseline GDP paths for each SSP. The mitigation costs are calculated using a regional Marginal Abatement Cost (MAC). While the global MAC curve is calibrated on the latest Assessment Report from the IPCC (AR6) (Byers et al., 2022), each region has its own MAC curve, which is calibrated on output data from the more complex process-based IAM IMAGE (more specifically, the TIMER energy module) (Van Vuuren et al., 2021). The absolute mitigation costs are then calculated by multiplying the area under the MAC by the baseline emissions.

The climate module consists of a linear relation between temperature and cumulative global emissions (Dietz & Venmans, 2019) following the TCRE relation (Transient Climate Response to Emissions), and the sea-level module comes from DICE 2016 (Nordhaus & Moffat, 2017). The damages are quantified using damage functions, split into sea-level rise and other damages (see next section on damages).

The model maximises total discounted utility and runs from 2020 to 2150 (but only results until 2100 are shown and used in this paper). As in previous versions of MIMOSA, utility is calculated with full inequality aversion, but without allowing for emission trading: each region pays for their own mitigation and damage costs, but costs in poor countries are weighted more strongly than costs in rich countries. This leads to higher carbon prices in rich countries than in poorer countries.

5.4.2. RCP targets

Originally, the RCPs were defined as pathways reaching a certain radiative forcing level, which in turn implied a temperature target. Since MIMOSA does not model radiative forcing directly, but only global mean temperature, we use the 2100 temperature levels from the original SSP scenarios (Riahi et al., 2017a) as calculated using the AR5 version of MAGICC6. More specifically, for each RCP, we take the median of the temperature value for all model-SSP combinations of that specific RCP. However, RCP 4.5 and RCP 6.0 do not reach their stabilisation radiative forcing of respectively 4.5 and 6.0 W/m2 in 2100: they only reach 4.28 and 5.49 W/m2. For that reason, we also impose a stabilisation temperature where we translate the stabilisation forcing levels to temperature targets using the MAGICC6 climate sensitivity relation and impose them as 2150 temperature targets. The resulting 2100 temperature targets and associated stabilisation temperatures are given in Table 2. RCP 8.5 was not used since it is only possible in SSP5 (Riahi et al., 2011b), and because of the recent general criticism in literature (Hausfather & Peters, 2020; Ho et al., 2019).

To match the original SSP pathways as closely as possible, the model does not take damages into account when calculating the emission pathway. They are instead calculated afterwards.

	Temperature in 2100	Stabilisation temperature
RCP 1.9	1.35 °C	1.35 °C
RCP 2.6	1.76 °C	1.76 °C
RCP 3.4	2.19 °C	2.19 °C
RCP 4.5	2.65 °C	2.76 °C *
RCP 6.0	3.30 °C	3.56 °C *

* Calculated using the MAGICC6 forcing-temperature relation

Table 2. Temperature targets for 2100 and 2150 *as calculated from the SSP-MIP scenarios.*

5.4.3. Damages and adaptation

The damage costs presented in the cost matrices in this study represent the sum of adaptation costs and residual damages, the damages which are not attenuated due to mitigation or adaptation measures. Given a regional adaptation level $l_r(t)$ for region r at time t, the residual damages $\mathrm{RD}_r(t)$ are defined as the remaining fraction of gross damages $\mathrm{GD}_r(t)$:

$$\mathrm{RD}_r(t) = \big(1 - l_r(t)\big) \cdot \mathrm{GD}_r(t) \tag{1}$$

Therefore, the total damages are equal to the sum of residual damages and adaptation costs:

$$\mathrm{D}_r(t) = \mathrm{RD}_r(t) + \text{Adapt. costs}_r\big(l_r(t)\big) \tag{2}$$

More specifically, the recent COACCH damage functions (Van Der Wijst et al., 2023) serve as basis for the damage estimates in this study. They provide regional damage functions based on bottom-up sectoral impact models using an internally consistent uncertainty specification. The climate impact sectors considered when creating the aggregate damage functions are agriculture, forestry, fishery, sea-level rise, riverine flooding, road transportation, energy supply and demand and heat stress on labour force. An added advantage is that sea-level rise damages are treated separately from other damages.

The sea-level rise damage functions, dependent on physical sea-level rise instead of global mean temperature, are provided for both the optimal adaptation case (containing adaptation costs) and the no-adaptation case. In this study, we interpolate between the two cases when using sub-optimal adaptation.

However, the COACCH damage functions do not treat planned adaptation explicitly for the other, temperature dependent, impact sectors. To still be able to use a gross damage function that captures the latest estimates of climate impacts, we select the damage function such that, when optimal adaptation is applied, the sum of adaptation costs and climate damage costs match the best estimates of the COACCH damage function. As shown in SI.3.2, the COACCH 95th percentile damage function (described as "high end" of the damage function) is a good proxy for the gross damage function: when optimal adaptation is applied, the global damage level is almost the same as the 50th percentile.

$$\mathrm{GD}_r(t) = \mathrm{COACCH}_{\mathrm{p95}}(T_t, r)$$

The adaptation costs, defined as:

$$\text{Adapt. costs}_r(l) = g_{1,r} \cdot l^{g_{2,r}}, \quad \text{with } l \in [0,1] \tag{3}$$

express the adaptation costs as a direct function of the *adaptation level* l (between 0, no adaptation, and 1, all damages are fully adapted to). While slightly newer functional forms of the adaptation costs exist (Agrawala et al., 2011; Bosello et al., 2010, 2013) that split the adaptation costs in stock and flow costs to represent planned and reactive adaptation, the overall adaptation costs remain the same. Due to the easier conceptual framework, the added numerical stability of the original method and the fact that for this purpose the difference between the two types of adaptation is not relevant, we have opted to use Eq. (3) for the adaptation costs.

The adaptation level l can be determined by an optimisation process that minimises the sum of residual damages and adaptation costs. However, this only yields the *optimal* adaptation level l^*. The actual projected adaptation level is likely to be substantially lower. Andrijevic et al. (2019) quantified this reduction factor by a time-dependent, SSP-specific, regional *adaptation readiness index*, also ranging from 0 to 1. An index of 1 means that full optimal adaptation is achieved, while an index of 0 means that no adaptation at all can happen. SSP1 and SSP5 see their adaptation readiness increase strongly over the century for almost every world region (Extended Fig. 1g), growing from a median of about 0.5 to about 0.75 in 2100, with some high outliers (Korea, Japan, Oceania, US, Western Europe, and Canada). SSP3 and SSP4, the SSPs with high challenge to adaptation, have adaptation readiness indices that grow much slower, with some regions even constant or declining index: most regions keep a readiness index between 0.3 and 0.5, with the same positive outliers as SSP1 and SSP5. The adaptation level is then equal to the product of the optimal level and the adaptation readiness factor (ARF):

$$l = l^* \cdot \mathrm{ARF}$$

5.4.4. SSPs

The Shared Socio-economic Pathways form the base of the socio-economic assumptions in the calculations in this paper: the regional baseline GDP paths, baseline emissions and populations are calibrated to the respective SSPs. While this data is only available until 2100, the period 2100-2150 is extrapolated with stabilisation in 2150, following common practice in previous literature (Gazzotti et al., 2021; Van der Wijst, Hof, van Vuuren, 2021). While the default MAC curve (SSP2) in MIMOSA is calibrated on the IPCC AR6 mitigation cost data, we apply a time-dependent and SSP-specific calibration factor to account for the different challenges to mitigation of the SSPs (Extended Fig. 1d). This factor is calibrated on output from the energy model TIMER (part of the IMAGE detailed-process IAM) (Van Vuuren et al., 2021; Van Vuuren, van Ruijven, et al., 2014). The SSP1 MAC curve becomes gradually cheaper than the SSP2 MAC over time, while SSP3 and SSP5 become relatively more expensive to mitigate. These SSP-dependent calibrations are independent of the cost reductions over time due to learning-by-doing, which were already implemented in the MIMOSA model.

5.4.5. Cost matrices

The cost matrices are created by calculating for each SSP-RCP scenario the net present value (NPV) of the mitigation costs and of the damages (residual damages plus adaptation costs) for the period 2020-2150 using Ramsey discounting. The NPV of a variable x (mitigation costs, damage costs, or GDP) are calculated as:

$$NPV(x) = \sum_t e^{-r_t t} x_t,$$

where r_t is the Ramsey discount rate at time t and equal to:

$$r_t = \mathrm{PRTP} + g_t \cdot \mathrm{elasmu},$$

with a Pure Rate of Time Preference (PRTP) of 1.5%/year and elasticity of marginal utility (elasmu) of 1.001, following the expert survey of Drupp et al. (2018) (Drupp et al., 2018). The yearly per-capita growth rate g_t is calculated for each scenario separately, as it is dependent on the GDP path. When calculating the absolute mitigation costs (Fig. 1.d), a fixed discount rate of 3%/year is used instead of the Ramsey discount rate to remove the effect of discounting when comparing mitigation costs.

A scenario for a single SSP-RCP combination is created in two steps. The first run calculates the cost-effective emission pathway and calculates the optimal adaptation level. The second run calculates the SSP and region specific reduced adaptation level by reducing the optimal adaptation level by the adaptation readiness factor, as well as the corresponding residual damages. This results in higher total damages, and represents the adaptation challenges in specific regions and SSPs.

Finally, for each SSP, a cost-benefit analysis (CBA) is performed with the same methodology of two runs: one with optimal adaptation, the second one with the reduced adaptation level.

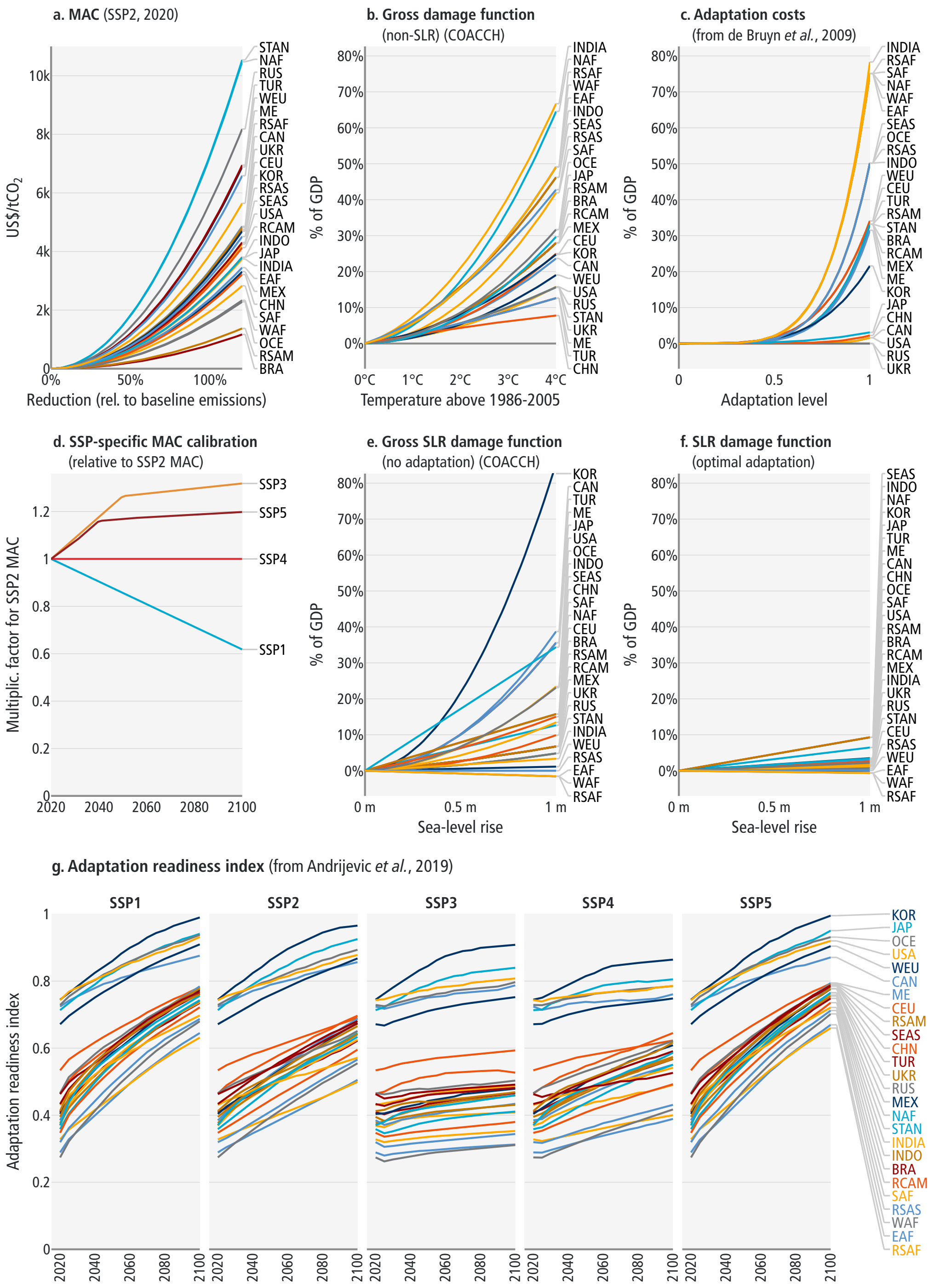
Code availability

The MIMOSA model is fully open source and available at https://github.com/kvanderwijst/Project-MIMOSA/tree/rcp-ssp-damage-matrix (and will be published to Zenodo at publication). The code to calculate the matrix values will be made available at publication.

Data availability

All the socio-economic data of the default MIMOSA model is freely available at https://github.com/kvanderwijst/Project-MIMOSA/tree/rcp-ssp-damage-matrix. The adaptation readiness index projections for each SSP are available at https://doi.org/10.1038/s41893-019-0405-0.

Extended figures



Extended Figure 1. Regionally dependent input factors.

Supplementary Information

The supplementary information is available online at:

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Equity principles, mitigation and climate impacts: balancing welfare and costs

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Under review

Equity considerations are crucial for successful international climate change policy. In this paper, several ways of incorporating equity in evaluating national climate targets are examined by comparing reduction targets resulting from the traditional cost-minimisation approach with those based on effort-sharing regimes and welfare optimisation taking into account not only regional differences in income, emissions and mitigation costs but also the latest insights in damage costs. We find that considering damage costs in effort-sharing regimes, leads to more stringent targets for developed regions like Europe and the USA compared to cost minimisation. One way to implement such schemes is via the use of flexible instruments, possibly leading to financial flows from emission trading of over 400 billion US$/yr in 2035. A welfare-maximising approach without emission trading is an alternative option, which leads results that reduce emissions and global inequality, with no financial transfers. Te downside is that global mitigation costs are higher due to the lack of emission trading. The reduction targets presented in this research can serve as input for updating national climate targets and presents ways to directly incorporate equity into Integrated Assessment Models scenarios often used by the IPCC.

6.1. Introduction

Determining fair and equitable climate targets for countries is crucial for informing the ratchet mechanism of the Paris climate agreement, through which countries submit increasingly ambitious Nationally Determined Contributions (Robiou Du Pont et al., 2016; Rubiano Rivadeneira & Carton, 2022; van den Berg et al., 2020). Doing so is very complex given large differences between countries in current (per capita) greenhouse gas emissions, their historical contribution to climate change, their capacity to reduce emissions, their vulnerability to climate change and their development levels. Model-based scenarios form an important tool to inform policymakers on complicated climate policy decisions. However, most of the scenarios currently submitted to the new IPCC AR6 scenario database (Byers et al., 2022) are based on Integrated Assessment Models (IAMs) operating under a cost-minimisation approach. This means that there is no explicit consideration of equity. This is based on the common assumption that the question of efficiency (lowest costs) can be separated from the question of fairness (who is paying for these costs), given the use of flexible instruments (like emission trading). Even so, it is important to note that cost optimisation itself does not lead to a just and equitable distribution: it typically leads to higher mitigation costs as a share of GDP for low-income countries, due to their higher emission intensity of the economy and the stronger reliance on coal (van den Berg et al., 2020).

The issue of a fair allocation in climate mitigation has been studied extensively in the literature, mainly by assessment of different effort-sharing regimes (Bertsimas et al., 2012; Du Pont et al., 2016; Höhne et al., 2014; Holz et al., 2018; Leimbach & Giannousakis, 2019; Okereke & Coventry, 2016; Pan et al., 2023; Robiou Du Pont et al., 2017; van den Berg et al., 2020). This literature has mainly focussed on target setting at the national or regional scale. Some studies also look at the economic consequences of implementation, either domestically or via emission trading by assuming a fully functional global emission trading market (Höhne et al., 2014; Holz et al., 2018; Pan et al., 2023; Robiou Du Pont et al., 2017; van den Berg et al., 2020). Most of this, however, only takes mitigation costs into account. This means that it ignores that countries can also be significantly impacted by climate damages, also leading to fairness considerations (De Cian et al., 2016; Hof, den Elzen, et al., 2010). Moreover, the literature pays very little attention to the implications of costs to welfare: a gain (or loss) of 1 USD leads to a larger change in welfare in low-income countries than in high-income countries. Therefore, in cost-benefit analysis, welfare is commonly assumed to have a non-linear relationship to income. If the same relationship were applied to the welfare implications of regional income differences, global welfare maximisation would automatically lead to a preference to reduce emissions more strongly in high-income countries.

This paper adds to the existing literature by examining fair regional reduction targets and corresponding mitigation costs based on 1) a full-costs approach (mitigation costs and damages) and 2) an approach that maximises welfare. Earlier, it was argued that five key fairness principles can be identified in the literature(van den Berg et al., 2020): equity, responsibility, capability, cost-efficiency and continuity. These can subsequently be translated into specific allocation mechanisms. Here, we examine a total of five distinct scenarios (Table 1). The first (1) scenario is the cost-minimizing approach without further redistribution of costs. This scenario (that is generally applied in IAM scenarios) corresponds to the principle of cost-efficiency. The subsequent three scenarios are based on (2) per-capita convergence of emission allowances (responding to the equity and continuity principles), (3) equal mitigation costs, and (4) equal mitigation plus damage costs (both corresponding to the equity and capability principle) (see Methods). In all these three scenarios, a fully functional global emission trading scheme is assumed as the targets resulting from these approaches are not realistically achievable domestically. The comparison of scenario 4 to scenario 3 shows the impact of including climate damages in the allocation. The fifth scenario (5) is based on a welfare-maximizing approach. In this scenario, the lower value to income in high-income regions leads to more ambitious domestic reduction targets in these regions.

We use the recent, open-source, simple cost-benefit Integrated Assessment Model MIMOSA (see Methods) to analyse the results of these regimes in terms of global and regional costs, the distribution of mitigation efforts and economic impacts across regions and implications for emission trading. Specifically, we explore how welfare optimisation compares to more traditional schemes such as cost-optimisation and effort-sharing approaches. The damage estimates are obtained using the new state-of-the-art probabilistic bottom-up damage functions from the COACCH project (Van Der Wijst et al., 2023). All calculations are done with a carbon budget of 500 $GtCO_2$, which is consistent with a medium likelihood of limiting global mean temperature change to 1.5 °C or less.

However, in the literature, mitigation pathways can also be calculated without imposing a global carbon budget, but by performing a cost-benefit analysis without fixed target. In this paper, we also investigate the impact of the different effort-sharing schemes and welfare representations on the global temperature target and global timing of mitigation. We thereby bridge the gap between effort sharing, inequality aversion representation and cost-benefit analysis.

6.2. Results

6.2.1. Results for 2035 for a fixed carbon budget

Cost minimisation

As all scenarios stay within a global budget of 500 $GtCO_2$, the only difference among the scenarios lies in the distribution of regional mitigation efforts or emission trading (Table 1).

	Name	Optimisation	Equity principle	Emission trading	Effort sharing scheme	Carbon budget
1.	**Cost minimisation**	Cost-minimising	No	No	No	500 $GtCO_2$
2.	**Per capita convergence**		Equality (in emission allowances)	Yes	Per-capita convergence of emission allowances (convergence in 2050)	
3.	**Equal mitig. costs**		Equality (in mitigation cost)	Yes	Equal mitigation costs (as % GDP)	
4.	**Equal total costs**		Equality (in total costs)	Yes	Equal mitigation + damage costs (as % GDP)	
5.	**Welfare**	Welfare maximising	Capacity	No	No	

Table 1. *Overview of the five scenarios used in this study when using a fixed carbon budget.*

Fig. 1 displays the regional emission reduction targets and costs (as a share of GDP) in 2035 for each scenario. In the cost minimisation scenario, there is a wide range of regional emission reduction targets (Fig. 1a), with a global average of 57% reduction compared to 2020 emissions and average mitigation costs of 1.7% of GDP (Fig. 1b). The regional differences in reduction targets compared to 2020 are influenced by two factors only in the cost minimisation scenario: (a) the cost-effectiveness of reduction measures in each region (represented by the regional Marginal Abatement Cost curve), and (b) the evolution of baseline emissions from 2020 to 2035. Regions with relatively affordable mitigation options (see Suppl. Fig. 1.1.1), such as South America (halting deforestation and increasing reforestation), have higher emission reduction targets (75% of 2020 emissions), while regions like the Middle East, Turkey and Central Asia have lower targets (around 40%). Mitigation costs vary significantly among regions: countries with a high carbon intensity are faced with higher costs. The mitigation costs of Sub-Saharan Africa are nearly three times higher than the global average, despite having a lower than average emission reduction target, due to the low GDP of the region. Conversely, Europe, with a low carbon intensity (Suppl. Fig. 1.1.1), incurs mitigation costs below 1% of GDP in 2035. Even so, in the long term income is distributed more equally than in the no-policy baseline because of the avoided climate change damages (Suppl. Fig. 1.2.3).

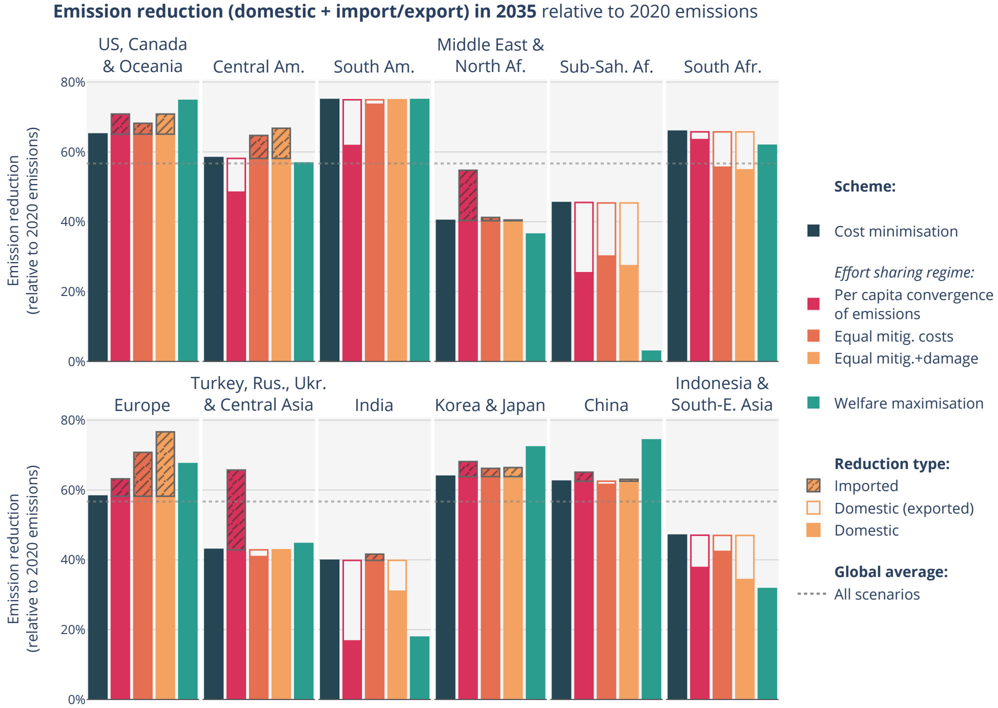

Figure 1a. Emission reductions per region in 2035. *Solid filled bars are the domestic emission reductions, that a region needs to achieve in the region itself, and pay for. Open bars are the exported domestic reductions: reductions that happen in the region, but are paid for by other regions. Striped bars are imported emission reductions: a region pays for mitigation abroad.*

Effort-sharing regimes

The emission reduction targets resulting from the different effort-sharing approaches deviate strongly from those resulting from cost minimisation. In our model, for each effort-sharing regime there is at least one region for which it is infeasible to achieve the resulting targets domestically. Therefore, we have assumed a fully functional global emission trading scheme in all effort-sharing scenarios.

A convergence towards equal per-capita allowances leads to higher reduction targets and subsequently mitigation costs for regions with high baseline per-capita emissions like Turkey, North and Central Asia and the Middle East. On the other hand, regions with low baseline per-capita emissions, like India and Sub-Saharan Africa, have much lower reduction targets. As a result, per-capita emission allocation leads to the lowest interregional income inequality by 2035 of all scenarios included in this study, but requires financial transactions of 730 billion USD in 2035 for emission trading.

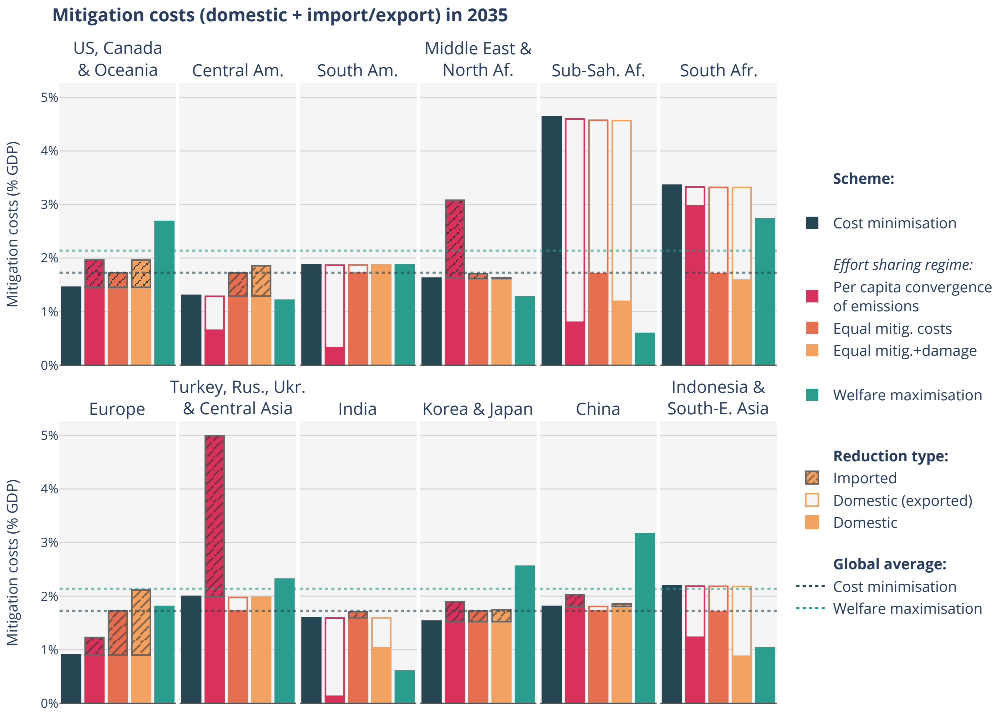

Figure 1b. *Mitigation costs in 2035, for the domestic reductions (solid colour), exported reductions (open bars) and imported reductions (striped bars). For reference, the global average of the cost-minimisation scenario is shown (which is the same as the three effort sharing regimes) (dark blue dotted line) and for the welfare maximisation scenario (green dotted line).*

Equalizing mitigation costs leads to reduction targets that are similar to cost minimisation in many regions, with some exceptions in the regions with the lowest and the highest GDP. In these regions, the fixed percentage of GDP allocated for mitigation results in relatively lower and higher absolute mitigation costs respectively, which translates to respectively lower and higher mitigation targets. While this method reduces interregional inequality slightly compared to cost minimisation (Suppl. Fig. 1.2.3), this approach entails significant financial transactions of over 300 billion USD in 2035 for emission trading. This is less than the per-capita convergence regime, but still constitutes more than 10% of the total mitigation costs (Table 2).

Equalizing mitigation costs overlooks incurred damage costs, which are notably unequally distributed over the world. When incorporating damage costs in the effort-sharing regime, the differences with cost-minimisation increase strongly. Regions like Indonesia, South-East Asia, and India benefit from this approach, while Europe has a large increase in mitigation effort compared to the cost-minimizing reference due to its relatively low climate damages and carbon intensity. Notably, interregional differences in mitigation costs are larger than in reduction targets, resulting in lower income inequality between regions compared to equalising mitigation costs and even larger financial transactions from emission trading, at 460 billion USD in 2035.

The per-capita convergence regime requires larger financial flows from emission trading than the equal mitigation costs and equal total costs regimes, as the former allocates allowances, independent of mitigation, while the latter two allocate reductions. When reductions are determined, every region has a minimum mitigation effort, based on its mitigation costs and incurred damages.

Combining mitigation costs, damages and capacity: welfare maximisation

The equal total cost regime yields an effort distribution that is significantly more equitable than cost-minimisation, since it considers both the costs of mitigation and the regional distribution of climate impacts. However, it leads to emission reduction targets that would very likely not be feasible to achieve domestically, leading to large financial flows due to emissions trading. Moreover, the method is focused on equalising costs and not on maximising welfare. The scenario based on welfare maximisation leads to a reduced mitigation effort in developing countries compared to cost minimisation, with targets that are feasible to achieve for all regions in our model. The targets are based on the marginal costs of mitigation, damages and per-capita income. In comparison to the equal total cost scenario, the welfare maximising scenario leads to substantially lower mitigation efforts for Sub-Saharan Africa (3% reduction vs. 28%) and India (18% vs. 31%). To offset this, OECD countries and China implement 5-15% more stringent reductions, resulting in 20% to 50% higher mitigation costs for these regions. The lack of emission trading increases the global mitigation costs from 1.7% of GDP to 2.1% in 2035. Welfare maximisation leads to very similar interregional income inequality in 2035 as for per-capita convergence.

As a sensitivity analysis, the reduction targets can also be calculated for a well-below 2°C carbon budget of 1150 $GtCO_2$ (SI 1.2.d). While all targets are slightly less stringent, the regional differences and differences between scenarios still remain. The financial flows from emission trading are slightly lower, but still large: 220 billion to 620 billion US$/yr in 2035 to over 1900 billion US$/yr in 2035. While the regional mitigation costs are also slightly lower, the damage costs are higher, leading to similar total costs. A further sensitivity is the level of damages: while we assume medium damages in the main text, Suppl. Fig. 1.2.10 shows the effect of a low or high damage function. Only the equal total costs and welfare scenarios are affected by the change in damages, leading to substantially less stringent mitigation targets for India, Indonesia and South-East Asia when the high end of the damage functions are assumed.

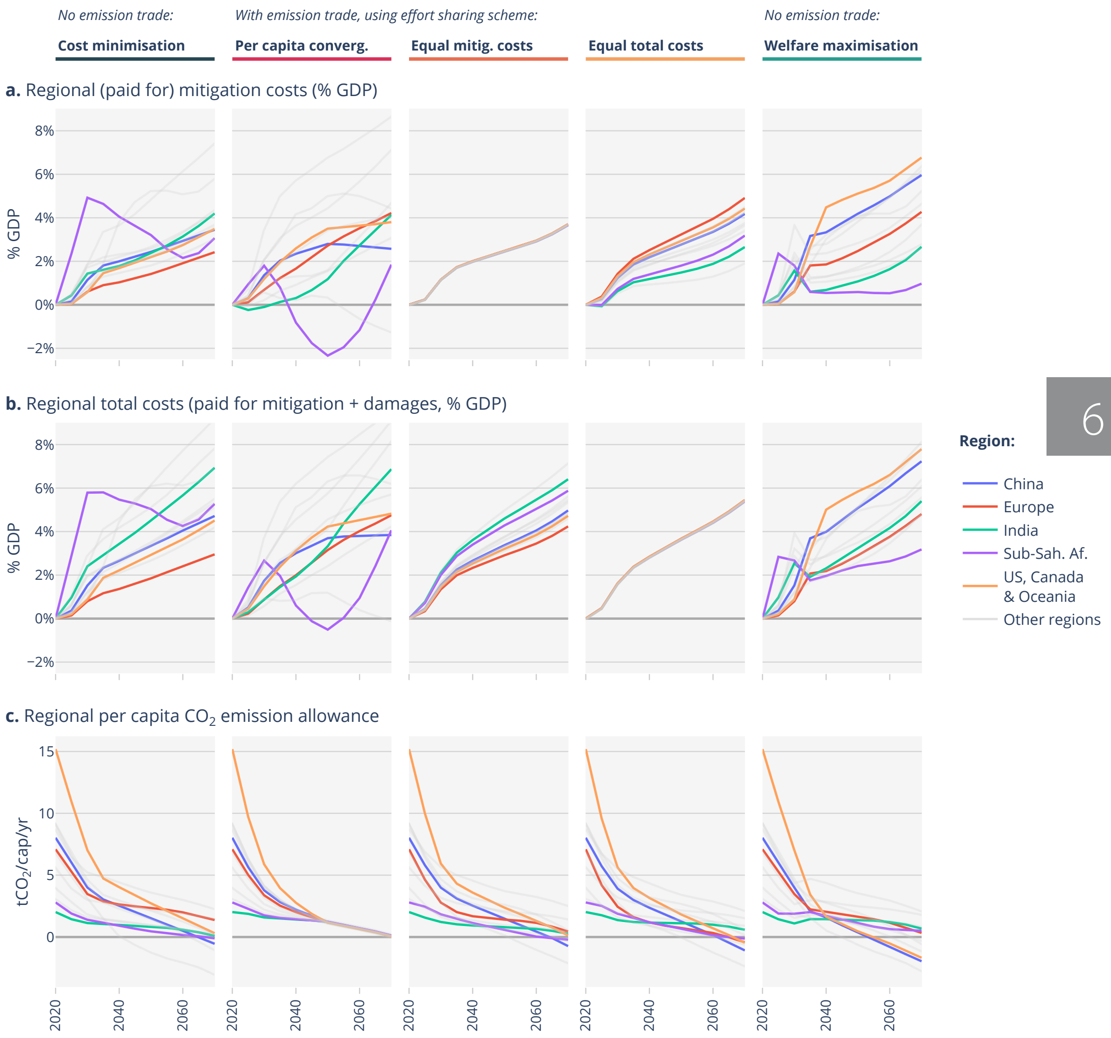

Figure 2. Evolution of regional mitigation costs (a), mitigation + damage costs (b) and regional per capita emission allowances (c) *for the 5 scenarios with carbon budget of 500 GtCO2.*

6.2.2. Results over time

Fig. 2 highlights the various perspectives on (in)equality over time: through mitigation costs only, total costs (including climate damages), and per-capita emission allowances. Per-capita convergence leads to equal per-capita allowances from 2050 onwards (or from 2025 onwards if immediate per capita convergence is used, see SI.1.2.e). While this leads in the short term to the lowest income inequality between regions, in the long term total costs are distributed unequally as this regime ignores damage costs and differences in mitigation costs.

Imposing equal mitigation costs still results in an inherently unequal distribution of total costs since damage costs are unevenly distributed across the world. However, richer regions generally have lower emission allowances per capita than regions with lower GDP, as wealthier countries tend to have lower baseline carbon intensity. These differences in per-capita allowances become even more pronounced when equal total costs are enforced, with regions like Europe, China, and the USA going deeply into net-negative allowances (but not necessarily emissions, as allowances can be traded) in the second half of the century.

The welfare scenario exhibits the most significant variation in mitigation costs, mostly because of differentiated regional carbon prices due to the lack of a global emissions trading system. Throughout the century, countries with high GDP per capita bear much higher costs than those with low GDP per capita, especially when the latter region also experiences high climate damages. Even when the sum of mitigation and damage costs are considered, countries with a relatively high per-capita GDP, like the USA, China and Europe, face significantly higher costs compared to regions with lower GDP per capita, such as Sub-Saharan Africa and India. This disparity is reflected in the income distribution across regions (Suppl. Fig. 1.2.3): after 2035, income is distributed more equally compared to the cost-minimising reference scenario, shown by an almost 10% lower inter-regional Gini coefficient by the end of the century compared to 2020.

The overall effect of the different equity schemes becomes even more apparent when considering the regional carbon budgets (Suppl. Fig. 1.2.2b), While the magnitude of these budgets depends on the size of the region, the differences between the scenarios depend on the regional characteristics (mitigation costs, damages, GDP growth, etc.) throughout the whole century. Compared to the 2035 reduction targets (Fig. 1a), which are still affected by regional inertia of mitigation and by relatively low climate impacts, the effect of climate damages becomes much more pronounced for regions like Indonesia and South-East Asia (with a budget over twice as large in the welfare and equal cost scenarios than in the cost-minimising scenario). Sub-Saharan Africa, however, has a very stringent carbon budget even in the total cost scenario, due to the relatively cheap mitigation options and rapid economic development in the second half of the century. The effect of the welfare maximisation becomes also more pronounced compared to cost-minimisation: the USA, Canada and China have a carbon budget of almost zero, compared to 80-110 $GtCO_2$ for these regions in cost-minimisation, whereas Sub-Saharan Africa has a carbon budget of 80 $GtCO_2$ in the welfare scenario, compared to almost zero in the other scenarios.

A summary of the equity implications of each scenario is shown in Table 2. The welfare scenario is the only scenario considering both capacity and regional differences in mitigation costs and climate impacts. In fact, the mitigation costs are 2 to 3 times larger in developed countries

<table>
<tr><th rowspan="2">Name</th><th colspan="2">Takes into account regional…</th><th colspan="2">Global mitigation costs
(in billion US$/yr, and % GDP)</th><th colspan="2">Global financial flows from emission trading
(in billion US$/yr, and % GDP)</th><th colspan="4">Regional mitigation + damage costs
(% of regional GDP)</th></tr>
<tr><th>…mitigation costs</th><th>…damages</th><th>2035</th><th>2070</th><th>2035</th><th>2070</th><th>2035 Europe</th><th>2035 India</th><th>2070 Europe</th><th>2070 India</th></tr>
<tr><td>Cost minimisation</td><td>Yes</td><td>No</td><td rowspan="4">2900
(1.7%)</td><td rowspan="4">12 450
(3.7%)</td><td>0</td><td>0</td><td>1.2%</td><td>2.9%</td><td>3.0%</td><td>6.9%</td></tr>
<tr><td>Per cap conv.</td><td>No</td><td>No</td><td>730
(0.4%)</td><td>2360
(0.7%)</td><td>1.5%</td><td>1.5%</td><td>4.8%</td><td>6.9%</td></tr>
<tr><td>Equal mitig. costs</td><td>Yes</td><td>No</td><td>310
(0.2%)</td><td>1020
(0.3%)</td><td>2.0%</td><td>3.0%</td><td>4.2%</td><td>6.4%</td></tr>
<tr><td>Equal total costs</td><td>Yes</td><td>Yes</td><td>460
(0.3%)</td><td>1960
(0.6%)</td><td colspan="2">2.4%</td><td colspan="2">5.4%</td></tr>
<tr><td>Welfare</td><td>Yes</td><td>Yes</td><td>3600
(2.1%)</td><td>14 050
(4.2%)</td><td>0</td><td>0</td><td>2.1%</td><td>1.9%</td><td>4.8%</td><td>5.4%</td></tr>
</table>

Table 2. *Summary of equity principles and financial flows of each scenario.*

than in developing countries, whereas the total costs are similar. The lack of emission trading, however, leads to a global increase in mitigation costs of 23% in 2035 and 14% in 2070.

In contrast, the equal total cost scenario follows a cost-efficient distribution of physical emission reductions, making it cheaper than the welfare scenario. Nevertheless, while this approach also results in substantially higher mitigation effort in developed than in developing regions, it necessitates financial flows of up to 2 trillion USD in 2070, or 0.6% of global GDP. OECD nations have to allocate around 1-2.5% of their GDP to emission trading abroad—significantly more than the 0.7% of Official Development Assistance (ODA) proposed in 1970. Additionally, this dependence on foreign emission reductions and trading might not align with the essence of the Nationally Determined Contributions (NDCs), which focus on domestic mitigation effort.

6.2.3. Equity and the optimal global target

While different representations of equity result in varying regional distributions of reduction efforts and costs, they can also impact the optimal global climate change target and timing of optimal global emission reductions. In this section, we analyse how strong this effect is by conducting a cost-benefit assessment.

In cost-minimisation setting, the optimal temperature target purely depends on the total costs and how those costs are distributed over time. In welfare optimisation, however, the regional distribution of costs also becomes important: finding the optimal target then means finding a balance between lowering the total costs and decreasing the regional inequality.

Using welfare maximisation without effort sharing regime results in a cost-optimal temperature target for 2100 that is 0.1°C lower than the target derived from cost-minimisation (Suppl. Fig. 1.3.1). As there is no emission trading, reducing inequality can only be achieved through differentiated mitigation efforts up to a certain point: beyond that, the additional mitigation costs become too high (Suppl. Fig. 1.3.2). Inequality can then only be diminished by reducing damages, hence the lower temperature target. Including effort-sharing regimes only has a very small effect on the cost-optimal temperature target compared to cost-minimisation due to the inclusion of emission trading and pre-defined regional distributions of mitigation effort: this is discussed in detail in Supplementary Information 1.3a.

6.3. Discussion and conclusion

Scenarios created by Integrated Assessment Models used by the IPCC are mostly based cost-minimising strategies without explicit consideration of equity. The research of this paper shows that regional emission reduction targets based on global cost-minimisation without trade lead to disproportionately high mitigation costs as share of GDP for developing countries, since regional targets are mainly determined by the cost-effectiveness of reduction measures in each region ignoring income differences. As developing regions also have higher climate change damage costs, cost-minimising strategies lead to total climate change costs of Sub-Saharan Africa which are 5 times higher than those of Europe by 2035, and for India this is 2.5 times higher.

Initial allocation of emission targets based on effort-sharing regimes leads to substantially different reduction targets and, if combined with emission trading, to more equal distributions of income across regions. Such regimes, however, also lead to large global financial flows from emission trading. A well-functioning global emission trading system is currently not in place. An alternative option to address equality in climate policy is incorporating damage costs and welfare considerations in target-setting, leading to less mitigation effort in regions with the highest impacts of climate change. This leads to a reduction of 3% compared to 2020 emissions for Sub-Saharan Africa, 18% for India, 68% for Europe and 75% for the USA. The trade-off is that, while this leads to higher global welfare, total mitigation costs are 10-25% higher than cost-minimisation.

The reduction targets presented in this research can serve as input for updated regional NDC targets that take into account equity, especially when using the equal total cost regime or the welfare-maximising approach. The current NDC targets for 2030, however, are still far below the ambition level required to meet the carbon budget of 500 $GtCO_2$ for all of the scenarios assessed in this paper (den Elzen et al., 2022) (see Suppl. Fig. 1.2.8)—with the exception of Europe. When strengthening ambitions, a broad perspective of mitigation costs, losses and damages, and regional capacity should be taken into account, which can be achieved by focusing on welfare maximisation.

6.4. Methods

6.4.1. MIMOSA

MIMOSA is a recent (Van Der Wijst et al., 2023; Van der Wijst, Hof, van Vuuren, 2021) open-source cost-benefit Integrated Assessment Model based on FAIR(Den Elzen & Lucas, 2005), written in the optimisation modelling language Pyomo (Bynum et al., 2021; Hart et al., 2011). It uses a Cobb-Douglas production function and has baseline emissions, total factor productivity and population calibrated on the Shared Socio-Economic Pathways (SSPs) (Riahi et al., 2017a). Mitigation occurs through a Marginal Abatement Cost (MAC) curve, which has been calibrated to reproduce the mitigation costs from the IPCC 6th Assessment Report WGIII scenario database. Each region uses the same global Marginal Abatement Cost (MAC) curve, but with a region-specific scaling factor calibrated using SSP2 MAC curves from the TIMER energy model, using the same methodology as in Ref. (Van Der Wijst et al., 2023). This scaling factor is obtained by comparing the carbon price per region required to reach 75% CO_2 reduction in 2050 compared to baseline, relative to the world average. The regional differences in marginal abatement costs stay constant over time: a region that has relatively cheap mitigation options now is assumed to keep relative cheap marginal mitigation costs throughout the century.

Temperature is calculated as linear function of cumulative CO_2 emissions using the TCRE relation, which has been shown to accurately reproduce temperature response (Dietz & Venmans, 2019). MIMOSA uses the DICE sea-level rise module (Nordhaus, 2014).

Damages are calculated using state-of-the-art COACCH damage functions (Van Der Wijst et al., 2023) for both sea-level rise and temperature related damages separately. These damage functions were through bottom-up sectoral impact modelling. While a wide range of sectors are covered (agriculture, forestry, fishery, energy demand and supply, labour supply, riverine floods, transportation and sea-level rise), important sectors like impacts on human health, biodiversity and tipping points are not included, leading to an underestimation of the damages.

While MIMOSA uses the 26 IMAGE regions (Van Vuuren et al., 2021), this paper opts to aggregate the results into 12 macroregions, in order to make the results more easily readable. See SI 1.1.b for the full definition of each macroregion.

6.4.2. Welfare-maximisation vs cost-minimisation

Most economic Integrated Assessment Models maximise discounted utility, where utility is a concave increasing function of per capita consumption. In a global model, without regional disaggregation, the standard welfare function is used, which gives the utility of year t as function of the elasticity of marginal utility η:

$$\text{utility}_t = \frac{1}{1-\eta}\left(\left(\frac{c_t}{p_t}\right)^{1-\eta}\right) - 1, \tag{1}$$

where c_t is the consumption in year t and p_t the population. When η approaches 1, the utility function converges to the logarithm of C_t. The model then maximises the Net Present Value (NPV) of the utility: the sum of the discounted utility.

Since MIMOSA has regional disaggregation, the welfare function needs to reflect the different regions. In literature, there multiple ways to calculate this. The default method calculates the NPV of the utility of the global average per capita consumption:

$$\text{NPV}_{\text{cost-min.}} = \sum_t e^{-t\rho}\left(\text{utility}\left(\frac{\sum_r c_{t,r}}{\sum_r p_{t,r}}\right) \cdot \sum_r p_{t,r}\right), \tag{2}$$

with ρ the pure rate of time preference (also called utility discount rate). This form is equivalent to using an inequality aversion parameter of 0, as commonly used in literature (Anthoff & Emmerling, 2019; Anthoff & Tol, 2010b; Berger & Emmerling, 2020; Gazzotti et al., 2021; Stanton, 2010; Tol, 2012), and quantitatively similar to using Negishi weights (Berger & Emmerling, 2020; Stanton, 2010). Since only the global average per capita consumption is considered, it does not matter in which region mitigation or damage costs occur: this leads automatically to a distribution of mitigation effort that minimises the costs.

However, this welfare representation clearly does not consider interregional consumption differences. An alternative formulation, presented in literature as having full inequality aversion, becomes:

$$\mathrm{NPV}_{\text{welfare max.}} = \sum_t e^{-t\rho} \sum_r \left(\text{utility}\left(\frac{c_{t,r}}{p_{t,r}}\right) \cdot p_{t,r} \right). \tag{3}$$

The main difference with the cost-minimisation approach is that the utility is calculated per region. Therefore, costs incurred in a less affluent region affect the welfare more than costs incurred in a rich region. Because of the concavity of the utility function, shifting money between regions to equalise per capita consumption simultaneously maximises the utility. However, as shown in this paper, if no emission trading is allowed, this means higher total mitigation costs, which in turn reduces the welfare.

In both welfare representations, we use a medium value of the pure rate of time preference of $\rho = 1.5\%/\mathrm{yr}$, and a default elasticity of marginal utility of $\eta = 1.001$, in line with default values of recent literature (Drupp et al., 2018; Gazzotti et al., 2021).

6.4.3. Emission trade

An emission trade module has been added to MIMOSA. The costs of domestic emission reductions are still calculated by the area under the MAC, as function of a regional carbon price. This determines the actual emissions of each region. When emission trading is allowed, or when the cost-minimising welfare function is used, the mitigation costs are minimised by implementing a global carbon price. This is not fixed exogenously in MIMOSA, but is a result of the optimisation process.

Emission reductions can be traded between regions. The price of imported or exported emission reductions on the global emission market is determined by the global carbon price. The change in mitigation costs is then determined by:

$$\text{mitig. costs}(t,r) = \text{area under MAC}(t,r) + \text{import/export cost balance}(t,r),$$

where the import/export cost balance is positive if a region imports emission reductions (or, in other words, pays for mitigation abroad), and negative when a country receives funding for domestic mitigation. The sum of the import/export cost balance globally is zero. For numerical stability, this constraint is implemented in MIMOSA as:

$$\sum_r \text{mitig. costs}(t,r) = \sum_r \text{area under MAC}(t,r).$$

Finally, the cost balance can also be expressed in terms of emission reductions by dividing by the global carbon price:

$$\begin{aligned}\text{paid for emission reduct.}(t,r) \\ &= \text{domestic reduct.}(t,r) \\ &+ \text{import/export cost balance}(t,r)/\text{global carbon price}(t).\end{aligned}$$

6.4.4. Effort sharing

This paper considers three effort sharing regimes: equal mitigation costs (as % of GDP), equal total costs (sum of mitigation costs and climate damages, as % of GDP) and per capita convergence of emission allowances. To quantify the latter regime, following van den Berg et al. (2020) (van den Berg et al., 2020), first the share of allowances per region is determined:

$$\text{share}(t,r) = \begin{cases} \left(\frac{t-2020}{2050-2020}\right)\cdot\frac{\text{pop}_{t,r}}{\text{POP}_t} + \left(1-\frac{t-2020}{2050-2020}\right)\cdot\frac{\text{emissions}_{2020,r}}{\text{EMISSIONS}_{2020}} & \text{if } t \leq 2050 \\ \frac{\text{pop}_{t,r}}{\text{POP}_t} & \text{if } t > 2050 \end{cases}$$

where POP_t and EMISSIONS_t are the global population and emissions respectively. Then, the allowances per region are calculated using:

$$\text{share}(t,r)\cdot\text{EMISSIONS}_t = \text{BASELINE}_t - \text{paid for emission reduct.}(t,r)$$

Supplementary Information

The supplementary information is available online at:

https://doi.org/10.5281/zenodo.8332333

Conclusions

7

7.1. Introduction

Since the start of the Industrial Revolution, humanity has increasingly emitted carbon dioxide (CO_2) and other greenhouse gases into the atmosphere through the combustion of fossil fuels, other industrial activity, and land use and land-use change (especially deforestation). As a result, the global mean temperature has increased by 1.1°C (the 2011-2020 period average) compared to pre-industrial levels (IPCC, 2023). Changes to the global mean temperature coincide with changes in extreme weather and lead to a range of wide-spread impacts on society, ecosystems and the economy across the world (IPCC, 2022a). Without climate policies, the global mean temperature could increase to over 3.4°C by the end of this century compared to pre-industrial times as a result of further greenhouse gas emissions (Riahi et al., 2022). This would lead to unprecedented, widespread and devastating impacts of climate change. The emission of greenhouse gases needs to be reduced drastically to limit these impacts. However, determining optimal climate (including the level of ambition) is very challenging, mainly because climate change is a long-term problem with many uncertainties and because damages are expected to occur unequally over regions and generations.

Model-based scenario analysis forms one way to help decision-makers to better understand the climate problem and possible response strategies. One specific form, cost-benefit analysis (CBA), focuses on the economic aspect of climate change by comparing the costs of mitigation (the costs involved to reduce greenhouse gas emissions) to the avoided climate impacts. The scenarios in this thesis are created using a so-called Integrated Assessment Model (IAM) of climate change. IAMs are computer models that aim to link the human aspects of climate change to the environmental aspects. IAMs vary in their technological and economic detail, the complexity of the represented geophysical processes, their regional scope and their methodological approach (e.g. simulation vs optimisation). In general, they can be classified into two main types: detailed process-IAMs and cost-benefit-IAMs (CB-IAMs). Detailed process-IAMs are typically large-scale, complex models with a high level of detail of the socio-economic and technological processes relevant to climate policy. These models typically only include some incomplete representation of impacts and damages of climate change. In contrast, CB-IAMs aim for a wider, more holistic approach: instead of only focusing on mitigation, these models focus on the interactions between climate policy, climate damages and adaptation, mainly from an economic perspective. In view of their broad focus, CB-IAMs typically have a less detailed representation of technological processes and a more stylized representation of the climate feedbacks. The first and most extensively researched CB-IAM is DICE, developed by Nordhaus in 1992 (Nordhaus, 1992a). Due to its transparency, accessibility and ease of extension, DICE continues to play a fundamental role in the literature on cost-benefit analysis of climate policy.

A key application of CB-IAMs is the calculation of cost-optimal global temperature targets and the social cost of carbon (an indicator for the optimal tax level for emitting greenhouse gases), or, at the very least, to understand what factors and uncertainties play a role in determining these quantities. The optimal target can be calculated by equalizing the marginal mitigation costs to the marginal damages: in other words, by finding the point at which a small additional amount of mitigation starts to cost more than the extra benefits of reduced climate damages (accounting possibly for adaptation). This analysis is highly dependent on estimates of mitigation costs, and of climate damages. Especially the latter is notably difficult to estimate. Partly for this reason, there has been strong variation in published cost-optimal temperature targets: from 3.1°C using the original DICE version in 1992, 3.5°C with the latest default version of DICE2016R2, all the way to 1.4°C when using different assumptions on discounting and the climate module (Hänsel et al., 2020).

Despite the extensive body of literature on costs and benefits of climate policy, several substantial knowledge gaps can be noted. First, limited attention is given to comprehensive uncertainty analyses. With some exceptions (Gillingham et al., 2018; Pycroft et al., 2011), comparing the relative uncertainty of the mitigation aspects, the climate impact aspects and the socio-economic developments in cost-benefit analysis is still missing. Second, no studies exist that have compared cost-minimising pathways with cost-benefit pathways using the same model framework—except for Nordhaus (2008), who did this for a few selected assumptions regarding discounting and climate targets. Third, both the data on mitigation costs and the data on climate impacts used by the main CBA-studies do often not reflect the latest scientific insights, which can lead to outdated results. Fourth, most current studies focus on economically optimal outcomes, which does not always lead to equitable outcomes. Most of the scenarios currently submitted to the new IPCC AR6 scenario database (Byers et al., 2022) are based on IAMs operating under a cost-minimisation approach. This means that there is no explicit consideration of equity.

7.2. Research aim and questions

As discussions and choices related to climate policies become increasingly important within society, there is a clear demand for science-based insights into the intricate interplays between mitigation policies and the effects of climate change. This research aims to address some critical policy questions and respond to the knowledge gap identified in the previous section by examining various aspects of cost-optimal climate policy. To that end, the main research question of this thesis is: **"How could climate policy be effectively designed on the basis of cost-benefit analysis, taking into account new insights in the costs of climate policy, the damages of climate change, and key uncertainties?"**

Given the broad scope of this topic, the main research question is divided into four sub-research questions:

1. What are the most relevant sources of uncertainty in cost-benefit analysis of climate change?
2. To what extent do new insights in climate damages alter the outcome of cost-benefit analysis, in particular the cost-optimal temperature target?
3. How do decisions regarding negative emissions and uncertainties in socio-economic development and related adaptive capacities, influence the cost-optimal emission trajectory?
4. How can equity and welfare considerations be combined with cost-optimality in determining regional emission reduction targets?

These research questions have been tackled using five research chapters. The relation between the chapters and the research questions is shown in Table 7.1.

	Chapter 2	**Chapter 3**	**Chapter 4**	**Chapter 5**	**Chapter 6**
	Uncertainty	New damage estimates	Overshoot	Adaptation	Equity
RQ 1: uncertainty					
RQ 2: new damage estimates					
RQ 3: negative emissions and adaptation					
RQ 4: equity					

Main focus of chapter. Addresses the RQ, but not the main focus.

Table 7.1. *Overview of the research questions and their relation with the research chapters.*

7.3. Main findings

1

What are the most relevant sources of uncertainty in cost-benefit analysis of climate change?

In the literature, there are two main methods to look at optimal emission pathways. The first looks at a given temperature target or carbon budget and identifies the most cost-effective way to meet this target. These cost-effective, or cost-minimising, scenarios, typically only minimise mitigation costs (e.g., optimal pathway to meet the 1.5°C target) (Table 7.2). The second method does not choose a target but derives it using cost-optimisation. This method, cost-benefit analysis (CBA), optimises the balance between mitigation costs and damages. Most of this thesis is focused on CBA outcomes. When we present outcomes using the first method (cost-effective scenarios), here, compared to most existing literature, we present a major innovation: we also consider damages in the optimisation process, even if the target is given—unless explicitly stated otherwise.

	Cost-effectiveness analysis		**Cost-benefit analysis**
Target	Set as part of analysis (e.g. temperature goal or carbon budget)		Outcome
Objective	Optimisation of costs (or welfare) under given target		Optimisation of welfare
Mitigation costs	Included		Included
Damages and adaptation costs	*Most literature:* Not included	*Here:* Included, unless stated otherwise	Included

Table 7.2. *Overview of the two main methods to look at optimal emission pathways.*

Box 7.1. Key concepts when determining the uncertainty in optimal climate policy

When designing optimal climate policy, several key factors need to be assessed. Five important ones are (1) mitigation costs, (2) damages from climate change, (3) discounting, (4) climate sensitivity, and (5) future socio-economic developments. They all have associated uncertainties that are relevant for optimal climate policy.

1. The mitigation costs indicate the costs of reducing emissions. The values and uncertainty range can be calibrated on the wide range of scenarios created by detailed-process Integrated Assessment Models used in IPCC AR6 Working Group 3 report, and is the result of varying assumptions on technology costs, efficiency of mitigation policies and many other underlying model assumptions.
2. The damage costs give an economic valuation of the impacts of climate change. This includes a wide range of positive and negative impacts, from sea-level rise to changes in agricultural yields. Since climate change impacts such a large amount of economic and non-economic aspects of our society, estimating its monetary impact is challenging, which results in large uncertainty. The ranges can be based on various estimates published in the literature.
3. The discount rates weigh the appreciation of costs over time. This is necessary as climate impacts happen over a large time-scale. Costs in the future can be seen as less important due to expected economic growth, the future is inherently more uncertain than the present, and an intrinsic preference for consumption now. This last factor is called the Pure Rate of Time Preference. Choosing a value for especially the latter factor is a long-lasting debate in economics and will always be a *normative* choice, based on judgement value and ethical considerations.
4. The climate sensitivity is a measure of how much the Earth warms up given a doubling of CO_2 concentration in the atmosphere. Its uncertainty, contrary to the discount rate, is purely geophysical. In this research, it is calibrated on the full uncertainty range of the IPCC AR6 Working Group 1.
5. Different socio-economic future developments (such as population and economic growth and political stability) also determine the outcomes of cost-optimisation. These are quantified by the Shared Socioeconomic Pathways: a set of five socioeconomic scenarios with diverging storylines that cover a wide range of assumptions (see Box 1.1).

Besides these five main aspects, this thesis considers various other sources of uncertainty: various assumptions on the amount of net-negative emissions, assumptions on effectiveness of adaptation, assumptions on equity, and model uncertainty.

When determining the cost-optimal temperature, the uncertainty is dominated by uncertainty in the damage function, followed by uncertainty in the discount rate and mitigation costs. The optimal temperature target depends on uncertainties in the damage function, mitigation costs, discounting, climate sensitivity and socio-economic development (see Box 7.1). The cost-optimal target ranges from 1.1°C to 4.4°C for all parameter combinations. In the literature, there has been a long debate on the importance of the discount rate. Interestingly, however, of these uncertainties, the damage function uncertainty is by far responsible for the highest variance in outcomes (58%, with temperature target ranging from 1.5°C to 2.9°C, all other aspects being medium), followed by the discount rate (15%) and the mitigation cost level (14%) (Figure 7.1a). Our analysis considers the full literature ranges for each parameter, contrary to many existing analyses which only perform a sensitivity analysis. When the high end of the damage function is assumed, the mitigation costs dominate the remaining uncertainty, since mitigation is highly necessary to reduce the damages. In contrast, the choice in the discount rate mainly determines the cost-optimal temperature target when the low end of damages is assumed, since discounting determines how much the far future—when the damages become significant even when assuming the low end of damage estimates—is valued. {Figure 7.1a, 2.2.2}

Uncertainty of temperature target dominated by damage function uncertainty, while carbon price initially mainly influenced by discounting, mitigation costs and damages

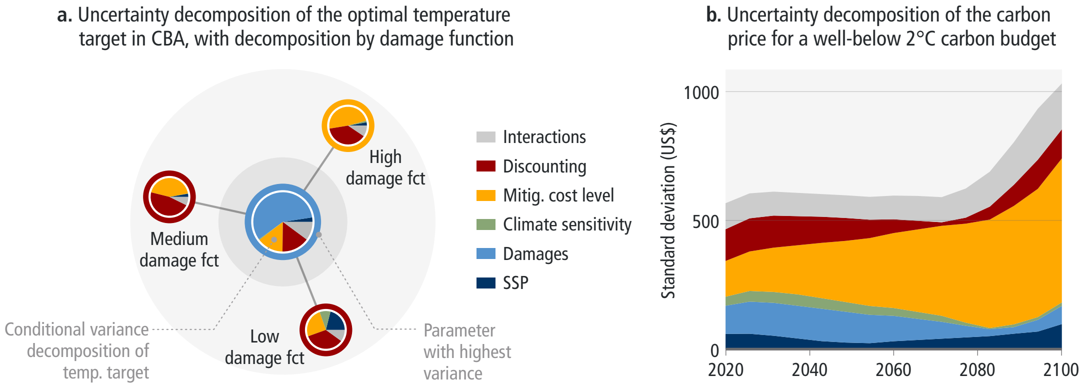

Figure 7.1. *(a) Uncertainty decomposition of the optimal end-of-century temperature using the same method, but in cost-benefit setting. The central node represents the decomposition using all parameters. The outer nodes are the result of a conditional variance decomposition, where the damage function is kept constant at a low, medium and high value. The parameter with highest variance is highlighted as the border of each node. (b) Uncertainty decomposition of the carbon price pathway required to reach a well-below 2°C carbon budget. {Figure 2.3, Figure 2.6}*

It is important to also accounting for damages in cost-minimising scenarios (e.g. with a carbon budget) as this determines the optimal emission trajectory. Typically, mitigation scenarios focus on minimum-cost pathways achieving the Paris Agreement without accounting for damages. This research shows that if damages were to be considered, this could double the required initial carbon price, shifting more of the mitigation effort towards the beginning of the century. The reason is that it is attractive to avoid unnecessary climate damages in the near future. Moreover, decreasing the pure rate of time preference from a medium value of 1.5% to a 0.1% also doubles the initial carbon price. This finding is also important for the analysis of cost-effective scenarios using detailed-process IAMs as normally looked at in IPCC assessments. {2.2.1, Figure 2.2}

The role of different uncertainties is somewhat different in cost-effective scenarios. Here, initially the discount rate, the mitigation costs, and the damage function are critically important. If damages are accounted for, the uncertainty in the carbon price is initially determined by the discount rate, the mitigation cost level and the damage function equally, while towards the end of the century, the uncertainty in the mitigation cost level dominates the total uncertainty. Consequently, the choice of discount rate and how climate damages are valued have a substantial effect on the carbon price in a cost-minimising setting. To reduce the uncertainty in current climate policy, the value of time preference needs to be chosen quickly, and our understanding of economic climate impacts needs to be improved. {Figure 7.1b, 2.2.1}

2 *To what extent do new insights in climate damages alter the outcome of cost-benefit analysis, in particular the cost-optimal temperature target?*

Current economic damage estimates cover a large range, with damage functions on the high end of the literature range (Burke et al.) being a factor 10 higher than the low end of the range (DICE). Moreover, a large part of the current cost-benefit literature still uses these outdated estimates of climate damages. In this thesis, we use for the first time a set of state-of-the-art damage estimates: the COACCH damage functions, named after the project in which they were developed. This section first compares these functions to those in existing literature, and, subsequently, applies them in cost-benefit analysis.

Box 7.2. Damage curves of climate change

In current literature, the economic impacts of climate change are typically modelled by either a bottom-up or a top-down approach. The top-down approach combines observed historical fluctuations in weather and (regional) economic output, to obtain empirical, data-driven damage estimates. While this approach is based on observed data, the associated uncertainty is still large as it is questionable if these relations hold far into the future. The bottom-up approach, on the other hand, considers the outcomes of physical impact models and/or expert judgement to quantify and aggregate the economic damages into a reduced-form damage function. However, these damage estimates are often incomplete, as they cannot cover all sectors where climate change might have an economic impact. Moreover, some impacts, such as on human health, biodiversity or ecosystems are by nature notoriously difficult to monetise. The damage functions of this type currently used by the literature are typically outdated and do not fully incorporate the current scientific knowledge of future climate impacts.

This thesis uses a set of new bottom-up damage functions that provide a higher level of regional detail than previous estimates. They provide internally consistent uncertainty ranges and are based on physical impacts derived from last-generation impact models.

These damage functions are created in three steps (Figure 7.3).

(i) Physical impacts are estimated by sectoral impact models. The impact sectors considered are agriculture, forestry, fishery, energy demand, energy supply, labour supply, riverine floods, transportation and sea-level rise. Some sectoral impacts are still lacking, like biodiversity losses, human health impacts and tipping points.

(ii) The physical damages are then translated to economic losses using the Computable General Equilibrium model ICES. This improves the transparency of how each type of physical is implemented in the economical assessment.

(iii) Finally, the economic losses from the CGE are combined and fitted with a closed-form relation for each region (typically quadratic). The COACCH damage functions allow decomposing the total GDP losses into (a) direct impacts from sea level rise, (b) direct temperature-related impacts and (c) indirect impacts from cumulated dynamic effects, e.g. through investment.

The COACCH damage functions are produced by monetising sectoral damages, have internally consistent uncertainty ranges and quantify regional SLR and non-SLR damages

Creation of the COACCH damage function and comparison to literature:

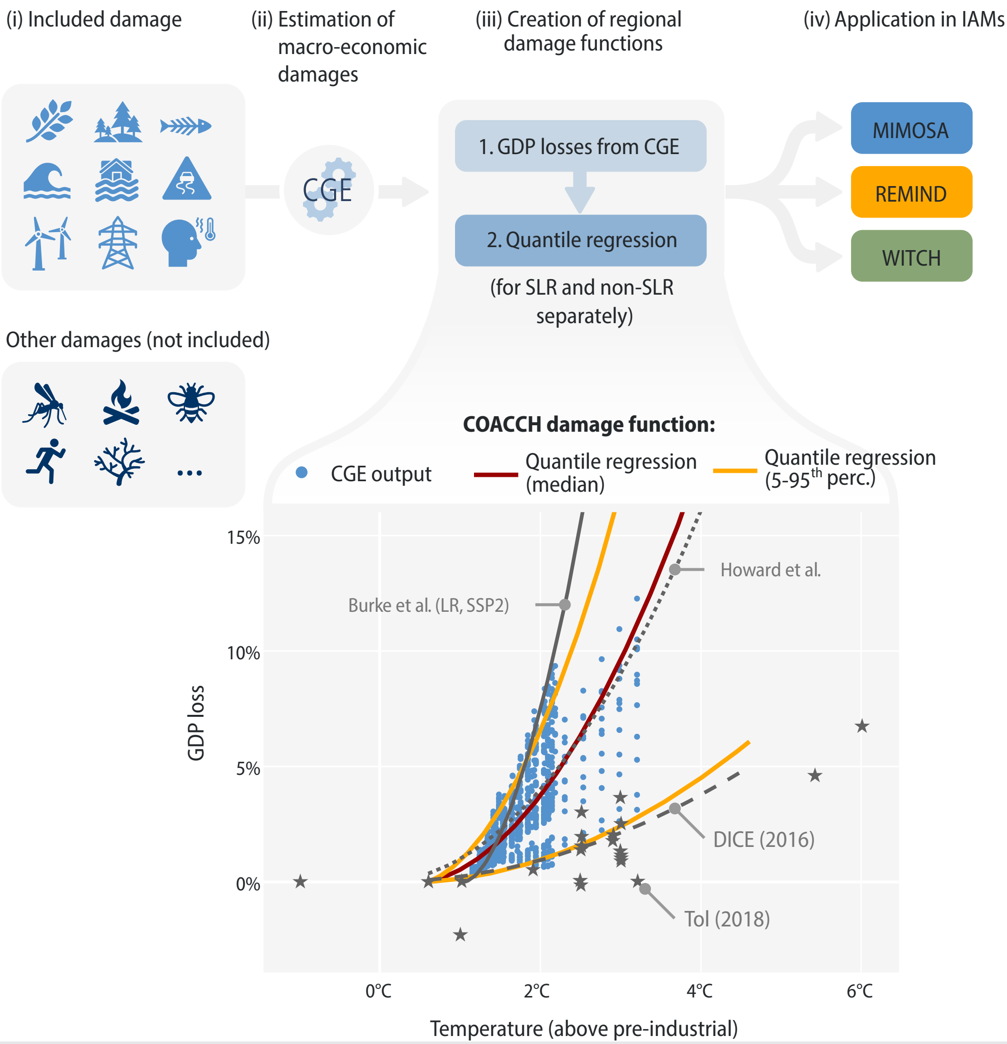

***Figure 7.2. Creation of the new COACCH damage functions**: output from sectoral impact models using a wide range of input variables are used as input for the economic valuation through the CGE model, which yields GDP losses. For each region, a quadratic function is fitted using quantile regression through the 5th, 50th and 95th percentiles. These damage functions are then used in the Integrated Assessment Models. {Figure 3.1, Extended Data Table 3.1, 3.2}*

The range in the new, internally consistent, COACCH damage curves are, when aggregated globally for the low, medium and high damage end representation, close to, respectively the DICE (2016), Howard et al. (2017), and Burke et al. (2015) damage functions. For 2°C warming above pre-industrial, the DICE, Howard and Burke damage functions, that previously spanned the literature range in damage function uncertainty, give damages of respectively 0.9%, 4.0% and 7.3% of GDP. The COACCH damage functions, when evaluated at their 5th, 50th and 95th quantile, yield 0.9%, 3.7% and 6.5% respectively (Figure 7.2). However, the methodology for creating the damage functions is completely different. While DICE also relies on bottom-up sectoral physical impacts, criticisms about these damage functions are the lack of empirical foundation, the relative simple monetisation method used, and that they are based on relatively old and scarce impact data. Top-down estimates, like the empirical Burke et al. damage functions, on the other hand, are criticised for their black box nature: the underlying impact drivers are unknown. The COACCH damage functions rely less on semi-qualitative expert assessment and use state-of-the-art physical impacts translated into economic damages. {Figure 7.2, 3.4}

Economic impacts of climate change vary strongly by region.

Regional economic impacts of climate change in 2100 at 3°C warming (RCP 6.0, medium damage estimates), when assuming optimal adaptation for sea-level rise:

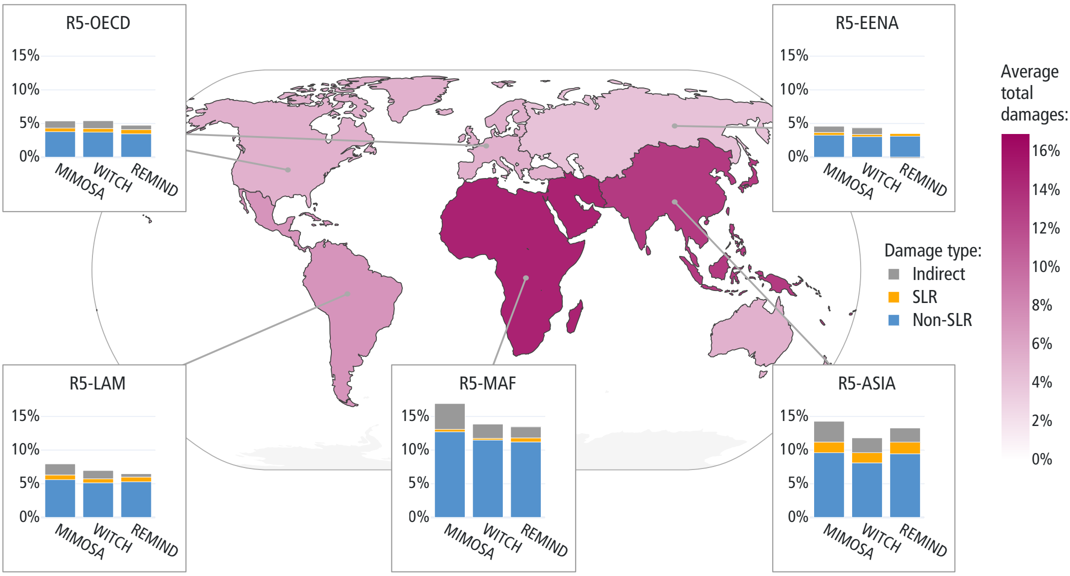

Figure 7.3. Economic climate impacts resulting from the damage functions by region and IAM*, for a fixed emission trajectory (RCP 6.0) and when using the medium damage function. Results are aggregated to IPCC R5 macroregions: OECD, Eastern Europe and Northern Asia (EENA), Latin America (LAM), Middle East and Africa (MAF), Asia. {Figure 3.2.a}*

On a global level, the GDP loss in the baseline RCP 6.0 scenario ranges from 10 to 12% at the end of the century when using medium damage (50th damage quantile) estimates, with substantial regional differences. The damages are significantly reduced in the mitigation scenario RCP 2.6 to 3.1-3.6% GDP loss in 2100. There are large differences in impact magnitude between regions (Figure 7.3). In RCP 6.0, the damages are the highest in the Middle East and Africa region, with total losses between 13% and 18% of GDP, followed by 12% to 14% for Asia. The other three macroregions have lower total damages. When disaggregating the macroregions further into model-native regions (12 to 26 world regions), the differences become even larger. Sea-level rise damages, even with optimal adaptation, make up a significant part (10-13% of total direct damages) in Asia and the OECD. Without adaptation to sea-level rise, the global total damages increase by over 30%, with substantially higher increases in the OECD—confirming the benefits of adaptation to sea-level rise. In a well-below 2°C scenario (RCP 2.6), the global GDP losses drop to 3.1-3.6% in 2100, with sea-level rise damages making up a much larger share of the total damages, especially in Asia and the OECD. The total damages become substantially higher when using the 95th percentile of the damage functions, with global damages of 18-22% of GDP in 2100 under RCP 6.0 and 5.7-6.6% of GDP under RCP 2.6. {Figure 7.3, 3.2}

7

These new estimates of climate damages lead to optimal temperatures below 2°C with central estimates of damages and discount rates, substantially lower than many previous cost-benefit studies. While assuming the high end of the damage function (estimated at the 95th percentile), the optimal temperature increase is close to 1.5°C in all

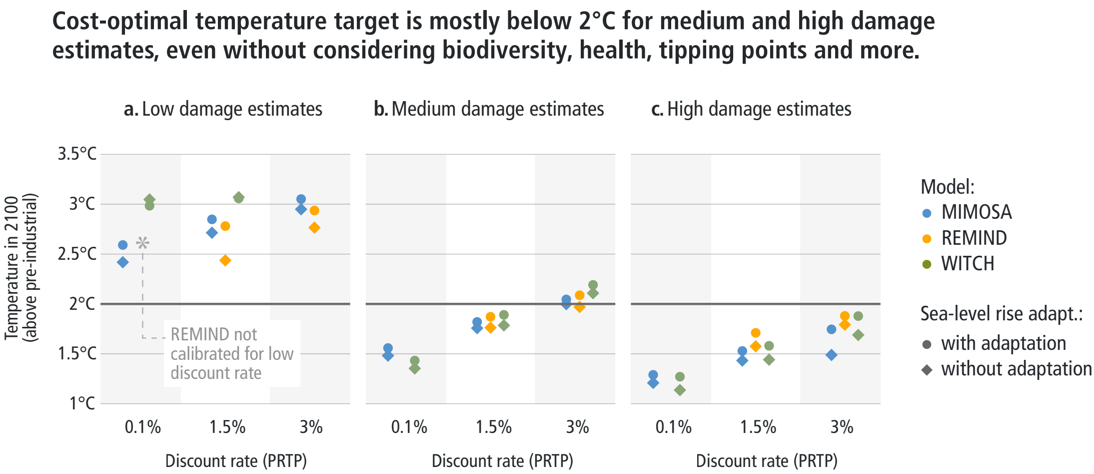

***Figure 7.4. Cost-optimal temperature target** for different levels of discounting, sea-level rise adaptation assumptions and damage function levels. {Figure 3.5}*

three IAMs considered in this research (MIMOSA, REMIND and WITCH). Since the COACCH damage functions do not include all impacts (e.g., biodiversity loss, health impacts and tipping points), the resulting temperature outcomes are likely to be conservative. This could provide justification to focus on the high end of the damage uncertainty (95th percentile as used in Chapter 3), especially when applying the precautionary principle. Therefore, this study gives strong economic validation of the Paris Agreement. {Figure 7.4, 3.3.1, 3.3.2, 3.4}

From a purely economic perspective, the benefits of reduced climate damages significantly outweigh the costs of climate policy. This is true even when some climate change damages, including those on biodiversity and health, and co-benefits from reduced air pollution, are not accounted for. Under medium assumptions of damages and discount rate, the Benefit-Cost Ratio is 1.5-3.9 for the three IAMs of this study. This presents an important case to improve societal acceptance of climate policy. The benefits, however, occur mostly in the second half of the century and beyond, while the mitigation costs mostly happen upfront, earlier in the 21st century. {3.3.3, Figure 3.6}

Uncertainty due to the use of different models is an important factor to consider in cost-benefit analysis. The analysis of Chapter 3 highlights that different models can lead to different results (Figure 7.4). While model uncertainty has a small impact on the cost-optimal end-of-century temperature target, it does impact the Benefit Cost Ratio significantly (1.5 for WITCH to 3.9 for REMIND), indicating the importance of including multiple models in a cost-benefit analysis. This means that the use of multiple models can highlight important differences and thus lead to more robust outcomes in the case of model agreement. {3.4}

3 *How do decisions regarding negative emissions and uncertainties in socio-economic development and related adaptive capacities, influence the cost-optimal emission trajectory?*

In the general literature on climate policy, there are several issues highlighted that so-far have not been studied well. This is important as these issues can have important policy implications. Here, we highlight two such topics: (1) negative emissions, and (2) socio-economic development and adaptive capacity.

First, we address assumptions on (net) negative emissions. Temperature targets can be interpreted as targets never to be exceeded, or as end-of-century targets that allow for a temperature overshoot mid-century that is compensated by net negative emissions later in the century. Given current societal and political debates on net-zero emission targets, but also the current lack of policy response, *this topic becomes increasingly relevant. Detailed-process IAMs have addressed this topic in more detail from a mitigation cost and (technological) feasibility perspective. However, the overall strategy on negative emissions while also accounting for damage costs has been given less attention.*

Some form of temperature overshoot (with net negative emissions later in the century) can be economically attractive, even when considering the extra damages due to additional climate change. The option to (temporarily) overshoot a climate target leads to increased flexibility and allows to shift some mitigation action (for some limited time) into the future, which lowers mitigation costs. However, it also creates some extra damages from climate change incurred during the period that the temperature target is exceeded. Under medium assumptions of damage function and discounting, the choice to avoid overshoot (and thus net negative emissions), and thereby interpreting the Paris Agreement target as a "no overshoot" target, leads to a sum of mitigation and damage costs that is around 13% higher than without the restriction. The outcome, however, depends on assumptions on mitigation costs, damages and discount rates. The cost differences are much smaller if mitigation costs are assumed to be relative small (compared to the literature median), damages high, or when a low discount rate is used. {4.2, Figure 4.1}

However, if a large part of the damage is not fully reversible, the attractiveness of negative emissions is much lower. The assumption that climate damages are not fully reversible significantly reduces the attractiveness of net negative emissions. Some climate impacts are likely reversible if global mean temperature goes down, such as reduced labour productivity or extra costs for cooling. Other impacts are not easily reversible, such as species loss or sea-level rise. Assuming that 50% of damages are irreversible leads to 50% lower total net negative emissions, since extra mitigation effort is required to reach the same maximum damage target when using net negative emissions. {4.3, 4.4}

All-in-all, this means that negative emissions are slightly less attractive if damages are taken into account, but they could still play some role in the overall mitigation strategy. Under a wide range of assumptions on damages, mitigation costs, time preference, reversibility of damages, we find that the attractiveness of negative emissions is much lower than often shown in scenarios based on optimisation of mitigation costs only. However, fully avoiding negative emissions leads to substantially higher costs, also when damages are accounted for. The required additional mitigation effort could also lead to feasibility issues.

Second, we address assumptions on different socio-economic trajectories and adaptive capacity. Given the current increased geopolitical tensions (through, for example, the Russian invasion of Ukraine), assessing a wide range of socio-economic developments becomes more and more important. The SSP-RCP matrix was developed specifically for this purpose (see Box 1.1 in the Introduction of this thesis). While the SSP-RCP framework has been used in the context of determining mitigation costs, it has never been used to do a comprehensive analysis of mitigation costs, adaptation and residual damage. Such analysis is presented here. This, in fact, requires a better understanding of adaptation. Also, adaptation is still poorly addressed in IAMs. It is known that adaptive capacity is highly dependent on socio-economic developments. In this research, we, therefore, first expanded the MIMOSA model to address adaptation and related this to factors that determine adaptive capacity. This allows us to systematically disentangle the effect of socio-economic developments on mitigation costs, adaptation effectiveness and adaptation costs, and residual damage costs. As such, we introduce "shared policy assumptions" (SPAs) for adaptation.

It is possible to improve the representation of adaptation in cost-benefit IAMs based on assumptions on adaptive capacity. Adaptation to climate change impact can lead to a decrease in (residual) damages, but leads to adaptation costs. The latter are normally considerably smaller than the avoided damages. Previous studies typically looked at two cases: an optimal adaptation case, where the costs of adaptation were weighed against the benefits of reduced residual damages, and a no-adaptation case. However, the level of adaptation is also highly dependent on the level at which countries are able to implement adaptation policies. In this research, this is quantified by a reduction factor that lowers the actual adaptation level below the optimal level. This factor is based on a time-dependent, SSP-specific, and regional adaptation readiness index recently published. The factor takes into account different governance levels for each SSP and country and is therefore a useful proxy for the different challenges to adaptation of each SSP. {5.1}

Assumptions on future socio-economic developments play a crucial role in determining optimal climate policy. The SSP-RCP matrix systematically shows high mitigation costs in the bottom rows (for the low RCPs) (Figure 7.5a) and high damage costs (including adaptation costs) in the top rows (for the high RCPs) (Figure 7.5b). The impact of socio-economic development (the columns for the SSPs) also substantially influences the costs, with SSP3 being the most costly on all aspects. By systematically comparing the costs of mitigation, adaptation, and residual damages for different socio-economic and climate scenarios, this research shows that the role of the SSPs (Shared Socio-economic Pathways) substantially impacts both the mitigation costs and damage costs, and is therefore important to consider when designing climate policy. {Table 7.3, Figure 7.5, 5.2}

	SSP1	SSP2	SSP3	SSP4	SSP5	Increases or decreases the costs?
Mitigation costs:						
Baseline emissions	Low	Medium	High	Low	Very high	Increases
Marginal abatement costs	Low	Medium	Very high	Medium	High	Increases
Reginonally differentiated carbon prices	Low	Medium	High	High	Medium	Increases
Absolute mitigation costs	Low	Medium	High	Medium	High	
GDP path	High	High	Low	Low	Very high	Decreases
Mitigation costs (as % of GDP)	**Low**	**Medium**	**Very high**	**High**	**Medium**	
Damage costs:						
Extra costs due to sub-optimal adaptation	Low	Medium	High	High	Low	Increases
GDP growth	Medium	Medium	Low	Low	High	Increases*
Timing of mitigation	Early	Medium	Medium	Early	Late	Decreases when earlier**
Damage costs (as % of GDP)	**Low**	**Medium**	**High**	**High**	**Medium**	

* Using Ramsey discounting slightly attentuates this affect

** Only has a very small effect on NPV (≤0.2% of GDP)

Table 7.3. Overview describing the main drivers of variation of mitigation/damage costs between the SSPs, *given a common climate target. {Table 5.1}*

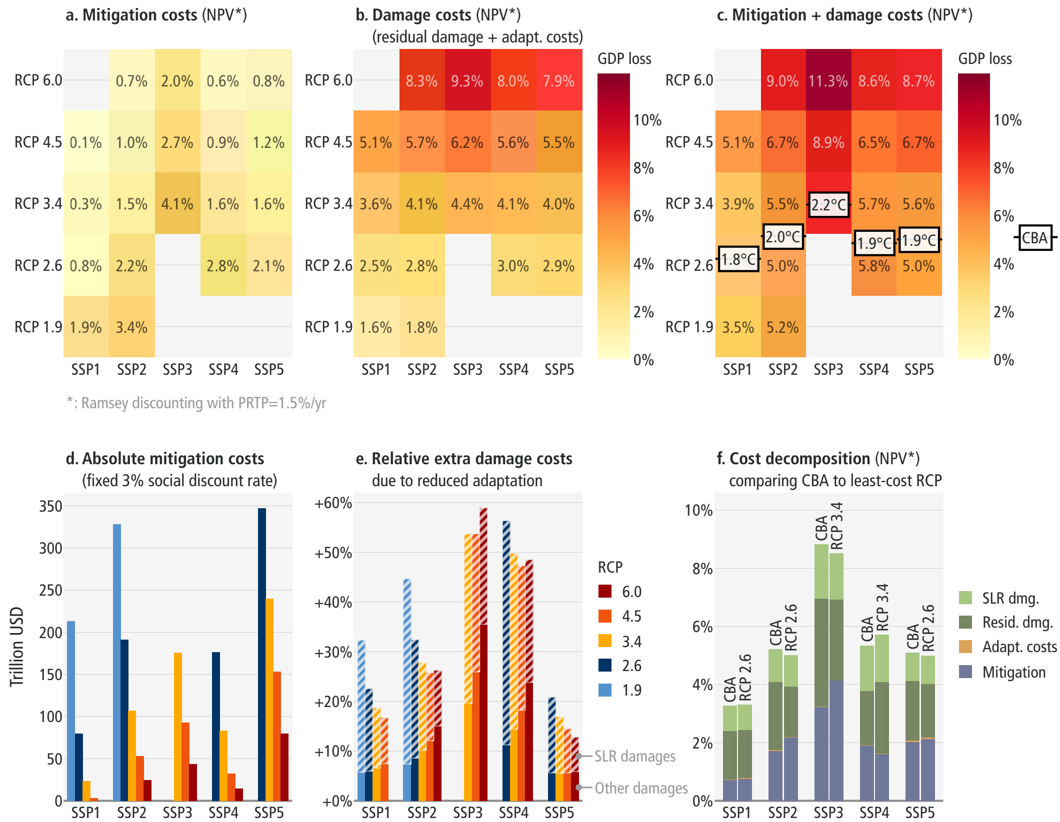

Figure 7.5. *SSP-RCP matrix for (a) the mitigation costs, (b) the damage costs (which equal the sum of residual damages and adaptation costs), and (c) the total costs (sum of (a) and (b)). The cost-optimal temperature target for each SSP is shown in (c), where the position in the y-axis corresponds to the translated radiative forcing target of that scenario. {Figure 5.1.a-c}*

The socio-economic assumptions included in the SSPs impact the mitigation costs through differences in (a) baseline emissions, (b) marginal abatement costs, (c) levels of regional differentiation in carbon prices, and (d) the GDP path. Mitigation costs can be an order of magnitude larger in SSP3 than SSP1. The absolute mitigation costs are determined by several factors that determine the challenges to mitigate, as also reflected in the SSP storylines (a, b and c) (see Table 7.3). The economic development (d) then determines the mitigation costs relative to GDP, shown in Figure 7.5a. The low baseline emissions, low marginal abatement costs and high level of global cooperation lead to mitigation costs of only 0.3% of GDP in SSP1 to limit forcing to RCP 3.4 (Net Present Value 2020-2150). The same target requires mitigation costs of 4.1% for SSP3 due to its high challenges to mitigation, combined with a low GDP path. Even though SSP5 is also associated with high challenges to mitigation—and therefore high absolute mitigation costs—the very high GDP path attenuates the relative costs of mitigation, with 1.6% of GDP for RCP 3.4. {Table 7.3 Figure 7.5, 5.2}

Introducing limits to adaptation as function of socio-economic development leads to are substantially higher damage costs than the optimal case. Damage costs, including adaptation costs, can be over 22% higher in SSP3 than SSP1. In this thesis, we introduce a notion of adaptive capacity as function of socio-economic development. In SSP1 and SSP5, with assumed low challenges to adaptation, the sum of residual damages and adaptation costs are 15% to 20% higher due to the assumed lack of adaptive capacity in some low-income countries than if optimal adaptation had been possible. For SSP3 and SSP4, with high challenges to adaptation, these costs are 50% to 60% higher than if optimal adaptation had been possible. The GDP path also affect the costs, even though damages are calculated as percentage of GDP: damages incurred when GDP is highest have a higher weight when calculating the NPV. This has a slightly attenuating effect on the total damage costs, since the SSPs with high challenges to adaptation also have a low GDP growth. The resulting total damage costs, including adaptation costs, for RCP 3.4 are 3.6% for SSP1, 4.4% for SSP3 and 4.0% for SSP5. {Table 7.3, Figure 7.5, 5.2}

A systematic use of the SSP-RCP matrix (as proposed by van Vuuren et al., 2012) can identify the optimal temperature, but also its dependence on the ambition of climate policy and socio-economic conditions. Using the SSP-RCP matrix, it is possible to compare for each combination of SSP and RCP the mitigation costs (Figure 7.5a) to the damage costs (Figure 7.5b) to obtain the total costs (Figure 7.5c). For each SSP, the RCP with lowest total costs gives an indication of the cost-optimal level of climate policy. A more precise way to calculate optimal climate policy is by performing a cost-benefit analysis for each SSP. The cost-optimal temperature targets found here vary from 1.8°C (SSP1) to 1.9-2.0°C (SSP2, SSP4, SSP5) and 2.2°C (SSP3) (for the damages included in the new damage functions). {Figure 7.5, 5.2.4}

Doing too much mitigation only leads to slightly higher mitigation costs, while doing too little can lead to much higher damage costs. The SSP-RCP matrix gives an indication of the economic risks of having a higher or lower target than the cost-optimal target. This risk is highly asymmetrical: more stringent targets than cost-optimal only lead to slightly higher mitigation costs, while less stringent targets can lead to much higher damage costs. For SSP2, the total costs (sum of mitigation, damage and adaptation costs) are only 5% higher for RCP 1.9 compared to the cost-optimal target, but up to 80% higher for RCP 6.0. {Figure 7.5, 5.2.4}

4 How can equity considerations be combined with cost-optimal climate policy in determining regional emission reduction targets?

So far, the research presented here has focused on global costs and temperature targets. Yet, climate policy is implemented at the national level, making it essential to determine the regional distribution of mitigation costs and damage costs. National implementation of climate policy depends on its perceived fairness. In the literature, there are different ways to deal with fairness. This thesis goes beyond that work by (a) systematically including the damages, and (b) focusing on welfare optimisation as an alternative method for determining regional reduction targets.

Box 7.2. The five different regional scenarios used in this research

The scenarios currently used by the IPCC have been criticised for the fact that they do not explicitly deal with equity but instead apply mainly cost-minimising strategies. The focus on global cost-minimisation is based on the common assumption that the question of efficiency (lowest costs) can be separated from the question of fairness (who is paying for these costs). The use of flexible instruments allows for financial transfers (like emission trading and effort sharing schemes). Most of the literature, however, only takes mitigation costs into account. This means that it ignores that countries can also be significantly impacted by climate damages – also leading to fairness considerations. There is also little attention to the implications of costs to welfare: a gain (or loss) of 1 USD leads to a larger change in welfare in low-income countries than in high-income countries.

Chapter 6, therefore, addresses these considerations by 1) taking a full costs approach (mitigation costs and damages) and 2) focusing on an approach that maximises welfare. To do this, we examine a total of five distinct scenarios. The first scenario is the cost-minimising approach without further redistribution of costs. This scenario (that is generally applied in IAM scenarios) corresponds to the principle of cost-efficiency. In the subsequent three scenarios, we add an explicit effort allocation. These principles are per capita convergence of emission allowances (responding to the equity and continuity principles), equal mitigation costs, and equal mitigation plus damage costs (both corresponding to the equity and capability principle). The fifth scenario is based on a welfare-maximizing approach, taking both mitigation costs and damages into account.

In the three scenarios with initial allocation (Scenario 2, 3, and 4) regions can either sell or import emission reductions for the existing carbon price. We do not combine the welfare-maximising scenario with emission trading (as this would automatically lead to a very large emission trading flow in order to equate per capita income in all regions). Scenarios with emission trading lead to a universal carbon prices, while restrictions on emissions trading result in differentiated regional carbon prices, reflecting regional differences in mitigation effort.

Regional emission reduction targets based on global cost-minimisation without trade lead to disproportionately high mitigation costs for developing countries. This inequality is even exacerbated if damage costs are taken into account. In cost-minimisation setting, regional targets for 2035, as percentage of 2020 emissions, are mainly determined by (a) the cost-effectiveness of reduction measures in each region, and (b) the evolution of baseline emissions from 2020 to 2035. Regions with relatively affordable mitigation options, such as South America (halting deforestation and increasing reforestation) and Europe, have higher emission reduction targets (75% reduction in 2035 relative to 2020 emissions for a pathway limiting warming to 1.5°C), while regions like the Middle East, Turkey and Central Asia have lower targets (around 40%). The resulting mitigation costs, as percentage of GDP, partly depend on the region's GDP: countries with relatively low GDP tend to have high mitigation costs. When combined with the damage costs in those regions, Sub-Saharan Africa have total costs (mitigation plus damages) in 2035 that are 5 times higher than Europe, and India 2.5 times higher than Europe. {Figure 7.6, Table 7.4, 6.2.1}

The regional reduction target for 2035 strongly depends on the equity representation.
Carbon budget: 500 $GtCO_2$

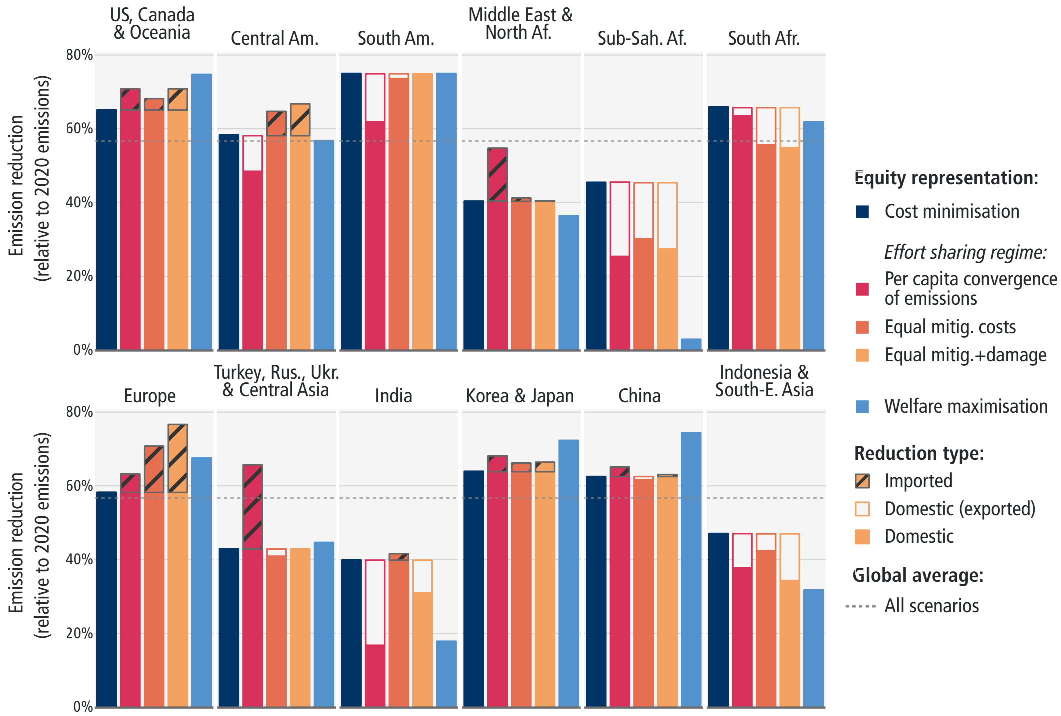

Figure 7.6. *Regional emission reduction targets for 2035, relative to 2020 emission levels, for the 5 equity representations of Chapter 6. The common global pathway used for each scenario is the cost-minimising pathway reaching a carbon budget of 500* $GtCO_2$.

<table>
<tr><th rowspan="3">Scheme</th><th colspan="2" rowspan="2">Takes into account regional…</th><th colspan="2" rowspan="2">Global mitigation costs
(in billion US$/yr, and % GDP)</th><th colspan="2" rowspan="2">Global financial flows from emission trading
(in billion US$/yr, and % GDP)</th><th colspan="4">Regional mitigation + damage costs
(% of regional GDP)</th></tr>
<tr><th colspan="2">2035</th><th colspan="2">2070</th></tr>
<tr><th>…mitigation costs</th><th>…damages</th><th>2035</th><th>2070</th><th>2035</th><th>2070</th><th>Europe</th><th>India</th><th>Europe</th><th>India</th></tr>
<tr><td>Cost minimisation</td><td>Yes</td><td>No</td><td rowspan="4">2900
(1.7%)</td><td rowspan="4">12 450
(3.7%)</td><td>0</td><td>0</td><td>1.2%</td><td>2.9%</td><td>3.0%</td><td>6.9%</td></tr>
<tr><td>Per cap conv.</td><td>No</td><td>No</td><td>730
(0.4%)</td><td>2360
(0.7%)</td><td>1.5%</td><td>1.5%</td><td>4.8%</td><td>6.9%</td></tr>
<tr><td>Equal mitig. costs</td><td>Yes</td><td>No</td><td>310
(0.2%)</td><td>1020
(0.3%)</td><td>2.0%</td><td>3.0%</td><td>4.2%</td><td>6.4%</td></tr>
<tr><td>Equal total costs</td><td>Yes</td><td>Yes</td><td>460
(0.3%)</td><td>1960
(0.6%)</td><td colspan="2">2.4%</td><td colspan="2">5.4%</td></tr>
<tr><td>Welfare</td><td>Yes</td><td>Yes</td><td>3600
(2.1%)</td><td>14 050
(4.2%)</td><td>0</td><td>0</td><td>2.1%</td><td>1.9%</td><td>4.8%</td><td>5.4%</td></tr>
</table>

Table 7.4. *Summary of equity principles and financial flows of each scenario.*

Introducing an initial allocation based on effort sharing regimes combined with emission trading leads to substantially different reduction targets and a more fair distribution of costs. Mitigation effort can be allocated following fixed principles to address fairness, while subsequently using flexible instruments like emission trading to enhance efficiency. The resulting distribution depends on the regime and equity principle. The per-capita convergence effort sharing regime leads to less stringent targets for regions with low per-capita emissions, like Sub-Saharan Africa and India (reduction of 17-25% relative to 2020 emissions). Equalizing mitigation costs leads to reduction targets that are similar to cost-minimisation in many regions, with some exceptions in the regions with the lowest and the highest GDP.

Incorporating damage costs in the effort-sharing regime leads to substantial differences with cost-minimization based on mitigation costs only. Regions like Indonesia, South-East Asia, and India benefit from this approach (reduction of 27-34% relative to 2020 emissions), while Europe has a large increase in mitigation effort compared to the cost-minimizing reference due to its relatively low climate damages and carbon intensity (77% reduction of 2020 emissions). The Gini index—measuring inequality between regions—for this scenario is also lower than that of equal mitigation costs only, highlighting the reduced inequality of the equal total cost effort sharing regime. {Figure 7.6, 6.2.1}

The scenarios with emission trading can lead to large global financial flows between regions. Directly implementing targets from the effort-sharing regimes would lead to concerns about regional sovereignty with potential feasibility risks, as achieving these targets requires substantial financial flows from emission trading, ranging from 730 billion US$/yr in 2035 to 2360 billion US$/yr in 2070 for the per capita convergence scenario, 310 billion US$/yr to 1020 US$/yr for the equal mitigation scenario, and 460 billion US$/yr to 1960 billion US$/yr for the equal total cost scenario. This dependence on foreign emission reductions and trading might not align with the essence of the Nationally Determined Contributions (NDCs), which focus on domestic mitigation effort.

The welfare-maximising scenario is the scenario considered here that takes into account differences in damage costs, in marginal mitigation costs, and in regional income levels. The non-linear, concave relation between costs and welfare that is commonly applied globally in cost-benefit analysis can also be applied regionally. This function represents the fact that a gain (or loss) of 1 US$ leads to a larger change in welfare in low-income countries than in high-income countries. The welfare of a country depends on its income level, but also on how much the regional GDP is reduced by mitigation costs and damage costs. This scenario cannot easily be combined with emission trading without additional effort sharing schemes, as this would automatically increase the amount of traded emissions in order to reach equal per capita consumption in every world region. As this is considered to be an unrealistic result, that scenario is not explored here.

The welfare-maximising scenario leads to lower mitigation efforts for regions with low income and high climate damages, and more mitigation effort for high-income regions with low damages. However, it also leads to slightly higher global mitigation costs. When maximising welfare, the mitigation effort in developing countries is further reduced. Compared to the equal total cost scenario, the welfare maximising scenario leads to substantially lower mitigation efforts for Sub-Saharan Africa (3% reduction relative to 2020 vs. 28%), India (18% vs. 31%) and Indonesia/South-East Asia (32% vs. 34%). To offset this, the targets for OECD countries and China are 5-15%-points more stringent, resulting in 20% to

50% higher mitigation costs for these regions. However, due to the differentiated carbon prices and absence of emission trading, the welfare scenario has 10-25% higher mitigation costs than cost-minimisation. {Figure 7.6, Table 7.4, 6.3.1}

Equity assumptions on regional distributions of reduction efforts do not only impact regional costs, but can also have consequences for the timing and global target of mitigation. If an equity regime influences global costs and how regional inequalities are weighed, the comparison of costs and damages at the global scale is also influenced—and thus the cost-optimal temperature target. In the welfare-maximising regime, the final optimal target is 0.1°C lower than the target derived from cost-minimisation without equity considerations. This mainly results from the inequality aversion of the welfare-maximising scenario: as there is no emission trading, reducing inequality can only be achieved through differentiated mitigation efforts up to a certain point. Beyond that, the additional mitigation costs become too high. Inequality can then only be diminished by reducing damages, hence the lower temperature target in this scenario. {Figure 6.3, 6.3.2}

7.4. Main conclusions

The goal of this thesis is to address the question: **"How could climate policy be effectively designed on the basis of cost-benefit analysis, taking into account new insights in the costs of climate policy, the damages of climate change, and key uncertainties?"** Answering the sub-research questions in the previous section allows to answer the main research question.

The uncertainty in climate change damage estimates is found to have a large impact on the optimal design of climate policy. This includes the optimal target, the optimal emission pathway over time, and the distribution of regional mitigation effort in a fair and equitable way. The uncertainty in climate damages was found to constitute the main source of uncertainty when determining the cost-optimal temperature target. This uncertainty is typically underestimated in the literature. After selecting a target, accounting for damages when calculating the emission pathway leads to a shift in mitigation effort towards the present to avoid damages incurred throughout the century, combined with a smaller temperature overshoot compared to an approach that does not account for damages. Once the global emission pathway is chosen, damages play a key role in determining how the regional mitigation efforts are distributed in a fair and equitable way, thereby reducing inequality caused by climate change.

Effective climate policy should consider key uncertainties when basing decisions on cost-benefit analyses. The uncertainty in climate damage estimates accounts for 50% of the uncertainty in determining the optimal temperature target, while the uncertainty in mitigation costs, the discount rate and the damage function account in equal parts for uncertainty in the initial carbon price in cost-effectiveness setting. Some of these uncertainties can be reduced by making normative choices (like the discount rate), or by applying decision making strategies that deal with uncertainty (like the precautionary principle in the case of climate damages), but designing policies should somehow take into account large remaining uncertainties.

The benefits from avoided damages outweigh the mitigation costs required to stay well below 2°C for almost all uncertainty estimates, except when damages turn out to be very low. In this thesis, we represented the uncertainty space for the key parameters determining the optimal temperature in the CBA calculations. If either medium or high damages are assumed, avoided damages exceed mitigation costs for well below 2°C for 95% of the cases looked at (Figure 7.7). The remaining 5% consists mostly of high mitigation cost scenarios. For a low damage function (such as the ones used in DICE), only 40% of all parameter combinations lead to higher benefits than costs for well below 2°C. Assumptions on the magnitude of the damages thus largely determines whether the benefits of well below 2°C outweigh the costs (much more than assumptions on the mitigation costs or the discount rate). These conclusions remain valid for the new COACCH damages functions: under medium assumptions of damages and discount rate, the Benefit-Cost Ratio is 1.5-3.9 for the same temperature target. The benefits, however, occur mostly in the second half of the century and beyond, while the mitigation costs mostly happen upfront, earlier in the 21st century. For the high end of the damage uncertainty, the cost-optimal temperature becomes 1.5°C, with a Benefit-Cost Ratio of 1.8-5.

This research provides strong economic validation of the Paris Agreement. Under medium assumptions of damages and discounting, the cost-optimal temperature is below 2°C, and for low discount rates or high damages, this drops to 1.5°C. The discount rate is a political choice on how to weigh damages and risks in the future. Regarding the uncertainty in damage estimates, the conclusion on the economic attractiveness of the Paris Agreement holds for a very large part of the uncertainty (range) (medium or high values). Since the damage functions used in this research do not account for sectors like biodiversity losses, human health impacts and tipping points, the cost-optimal temperature target is likely to be substantially lower than the medium estimates. Moreover, co-benefits of mitigation, like reduced air pollution from fossil fuel combustion, make the more stringent targets even more economically attractive.

The benefits from avoided damages outweigh the mitigation costs required to reach a 2°C target for almost all parameter combinations, except when damages are low.

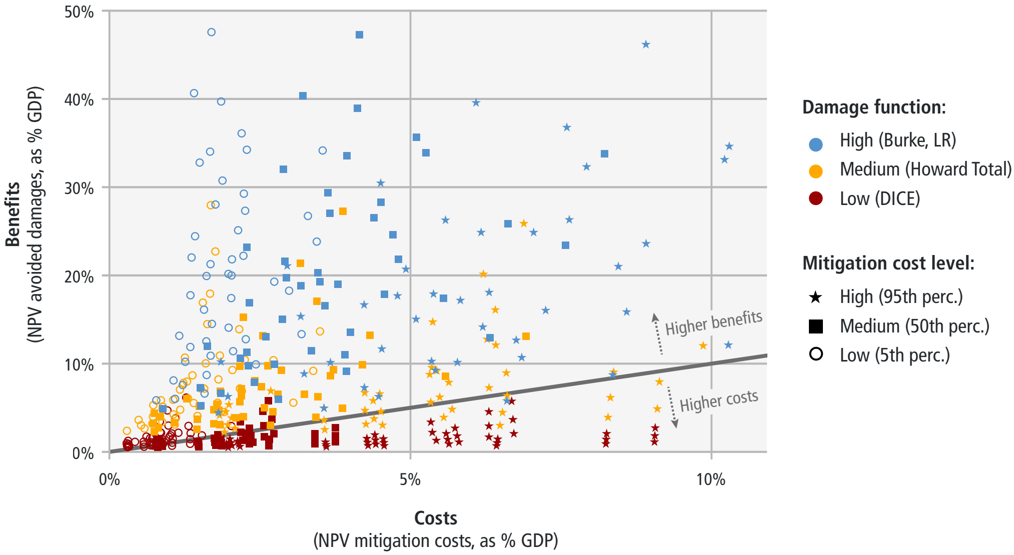

Figure 7.7. *Benefits of avoided damages (y-axis) compared to mitigation costs (x-axis) for each combination of the parameters used in Chapter 2. Scenarios above the y=x axis have higher benefits than costs. Both costs and benefits are expressed as net present value (2020-2100), relative to GDP. Note that the benefits would increase if the time horizon would be extended to 2150 due to the nonlinear increase in damages in the baseline scenario. {Figure 2.4}*

Cost-benefit analysis is a useful tool to support climate policy assessment, but requires up-to-date estimates of climate damages and mitigation costs, needs a clear and transparent incorporation of key uncertainties, and should be complemented with more specialised and detailed tools to design effective climate policies. Designing effective climate policy requires a careful balance of the key aspects of climate change and policy. Climate damages are key in most aspects around climate policy: from target setting to distributional issues. Cost-benefit analysis and CB-IAMs provide transparent insights into the interactions between these aspects. However, to be policy-relevant, the models should be calibrated to the latest scientific insights and have a clear incorporation of the relevant uncertainties.

7.5. Research recommendations

The climate change damages are found to play a significant role for the optimal outcome of many aspects of climate policy. Therefore, climate damages should be taken into account also in detailed-process Integrated Assessment Models when constructing scenarios. Moreover, narrowing the range of damage estimates will help to narrow the outcomes of cost-benefit analysis. Most current detailed-process IAMs do not consider climate damages when creating global emission pathways. However, incorporating these damages directly into the model leads to a shift in mitigation effort towards the present, and less reliance on large-scale net negative emissions at the end of the century. More research into the economic costs of climate change, including the costs and effectiveness of adaptation, should be performed to reduce the current uncertainty ranges.

Equity considerations should be directly addressed in mitigation scenarios. Welfare-maximisation provides a promising way to derive targets compared to cost-minimisation, especially since climate impacts are distributed so unevenly over the world. Scenarios produced by IAMs have been criticised for their lack of equity representation. A shift towards welfare-maximisation instead of purely minimising mitigation costs is an effective way to address equity in climate policy. Other ways are through effort sharing regimes. These regimes, however, should also consider climate damages if aiming to provide a full overview of the regional costs and benefits.

Using the full literature uncertainty ranges in cost-benefit analysis provides more robust analysis of policy-relevant outcomes than traditional sensitivity analyses. Sensitivity analyses typically give an underestimation of the total uncertainty, since they don't use the full literature range on key aspects of climate policy. A useful tool to provide robust analysis of large ensembles of IAM scenarios is through a Sobol decomposition of the variance in relevant variables: the total variance is split in partial variances attributed to each parameter, along with interactions between them. Since sampling from a continuous distribution would require thousands or millions of runs—which is computationally infeasible—the distribution can be approximated by discrete distributions. Then, using a Monte Carlo approach, the Sobol indices can be calculated efficiently.

More sectoral impacts should be integrated in current damage functions. The COACCH damage functions still lack many sectoral impacts, like biodiversity losses, human health impacts and tipping points. Therefore, the resulting damages are likely to be an underestimation of the actual damages.

The transparency of damage functions can be further improved by incorporating sectoral damages directly into Integrated Assessment Models. The COACCH damage functions are created through an intermediate step of monetisation through a Computable General Equilibrium model. While this accounts for some interactions between sectors and implicit market-driven adaptation, the sectoral disaggregation gets lost when using the resulting damage functions in an IAM. Using the physical climate impacts directly in IAMs could lead to more transparent results, and to more interactions with the mitigation technologies already modelled by the IAMs.

Adaptation needs to be better modelled to design effective climate policy that combines mitigation, impacts and adaptation. While there are many case-studies on local adaptation projects, the research on adaptation costs and effectiveness with a global coverage are mostly outdated.

Modelling equity considerations in international climate policy requires a high resolution in the number of countries/regions that are represented. In fact, it would be important to also incorporate differences between income groups within a region. A high regional granularity is important when modelling climate policy, since climate damages and mitigation costs vary widely by region. Various equity aspects disappear when the regions are too large: country-level analyses would be necessary to be the most policy relevant. However, even with high regional detail, differences between income groups within regions can be important.

Box 7.3. Ongoing research with the MIMOSA model

The MIMOSA model has seen several major development steps throughout this thesis. But the work doesn't stop here. Currently, several extensions are under development in the context of other research projects and collaborations, aiming to make MIMOSA more complete and policy-relevant. A first project involves extending the representation of emissions from only CO_2 to a representation of also other greenhouse gases (first of all methane) to research the effect of different reduction strategies for different gases (e.g. in relation to the estimate of the Global Warming Potentials). In a second project, the co-benefits of mitigation through reduced outdoor air pollution from fossil fuel emissions is being researched, as well as its impact on cost-benefit analysis. A third project is developing a circular economy module for MIMOSA, to analyse the various choices in material (re)use and efficiency improvements.

7.6. Policy recommendations

Ambitious climate policy is economically attractive. The thesis shows that for ambitious goals the avoided climate damages far outweigh the mitigation expenses. The cost-optimal temperature target is close to 1.5°C or lower. The benefit-cost ratio in a cost-optimal scenario is 1.5 to 3.9 for medium assumptions on discounting and damages, which would be even higher if missing sectors were taken into account (like human health, biodiversity, reduced air pollution). Most of the benefits, however, happen later in the century, with a break-even point around 2050 where the yearly benefits start to surpass the mitigation costs.

Given the large uncertainties in key aspects of climate policy and climate change, a risk-minimising strategy is preferrable over a middle-of-the-road cost-optimal target. The level of climate damages is the main source of uncertainty when determining a temperature target in cost-benefit setting. The risk that damages are higher than the current, conservative, middle-of-the-road estimates warrants more stringent climate action. Moreover, the extra mitigation costs of too stringent climate action are small, especially compared to the extra damage costs when too little climate policy is implemented.

Climate impacts are not equally distributed across regions. It is therefore important to also take damages into account when considering equitable distributions of mitigation effort. While many current effort sharing regimes focus on mitigation costs, the aspect of climate impacts should also be taken into account.

Using a welfare-maximising approach instead of cost-minimisation leads to higher mitigation effort for developed regions, and less strict targets for developing regions. Welfare-maximisation results in less inequality, since it considers regional differences in income, in marginal mitigation costs, and in climate damages.

In conclusion, we have shown that climate mitigation is more than worth it economically. The tools to reduce emissions exist, the technology exists. It is now time to act on it. Every action matters and is important to reduce the impacts of climate change. Acting today is better than tomorrow, and tomorrow better than the day after.

Samenvatting

8.1. Introductie

Sinds het begin van de industriële revolutie heeft de mensheid steeds grotere hoeveelheden koolstofdioxide (CO_2) en andere broeikasgassen uitgestoten in de atmosfeer. Het verbranden van fossiele brandstoffen en veranderingen in landgebruik (waaronder ontbossing) zijn de belangrijkste oorzaken hiervan. Hierdoor is de gemiddelde temperatuur van de atmosfeer gestegen met 1,1°C ten opzichte van het pre-industriële tijdperk. Deze temperatuurstijging heeft nu al gezorgd voor extremer weer en heeft over de hele wereld grootschalige gevolgen voor onze maatschappij, de ecosystemen en de economie. Zonder klimaatbeleid zou de mondiale temperatuurstijging tegen het eind van deze eeuw kunnen oplopen tot boven de 3,4°C. Dit zou leiden tot ongekende, verwoestende, en wijdverspreide gevolgen door klimaatverandering (IPCC, 2022b). De uitstoot van broeikasgassen moet drastisch verminderd worden om deze gevolgen te beperken. In welke mate en hoe snel dit precies gedaan moet worden is echter ingewikkeld te bepalen, omdat klimaatverandering een langetermijnproces is met veel onzekerheden, en omdat de kosten van klimaatbeleid en de gevolgen van klimaatverandering ongelijk verdeeld zijn over regio's en generaties.

Scenario-analyses kunnen beleidsmakers helpen met het beter begrijpen van het klimaatprobleem en het in kaart te brengen van mogelijke oplossingsstrategieën. Een specifieke vorm hiervan is de kosten-batenanalyse. Hierbij ligt de focus op de economische aspecten van klimaatverandering door de kosten van klimaatbeleid te vergelijken met de baten van verminderde klimaatschade als gevolg van dat beleid. Dit proefschrift concentreert zich op dergelijke analyses, gebruik makend van Integrated Assessment Models: computermodellen die de socio-economische aspecten van klimaatverandering koppelen aan de geofysische aspecten. Dit soort modellen worden al sinds de jaren '90 ontwikkeld (waaronder het bekende DICE-model van Nordhaus uit 1992), en spelen nog steeds een belangrijke rol in de literatuur over de kosten en baten van klimaatbeleid.

Box 8.1. Kosten van klimaatschade en kosten van klimaatbeleid

In dit proefschrift behandelen we meerdere soorten kosten die te maken hebben met klimaatverandering. Allereerst de kosten van **klimaatschade**, ook klimaatimpacts genoemd. Klimaatverandering zorgt voor schade aan de maatschappij, het milieu en de economie. Een deel hiervan kan worden uitgedrukt in monetaire schade: kosten door overstromingen, verloren oogsten door droogte, verlaagde visopbrengsten, schade door bosbranden, verminderde arbeidsproductiviteit tijdens hittegolven, enzovoorts. In de literatuur worden deze kosten vaak gegeven als schadefuncties: economische kosten (als percentage van het bruto nationaal product) als functie van mondiale temperatuurstijging. Een ander deel is lastiger uit te drukken in geld: verlies van biodiversiteit, mensen die moeten vluchten door langdurige droogte, opkomst van ziektes als malaria, enzovoorts.

Klimaatbeleid kan deze effecten verminderen. Klimaatbeleid bestaat uit zowel klimaatadaptatie (het aanpassen aan klimaatverandering) als klimaatmitigatie (het verminderen van de uitstoot van broeikasgassen). Voorbeelden van klimaatmitigatie zijn het plaatsen van windmolens en zonnepanelen, het isoleren van huizen, efficiënter maken van de landbouw en het tegengaan van ontbossing. Voorbeelden van klimaatadaptatie, daarentegen, zijn het bouwen van hogere dijken tegen zeespiegelstijging, landbouw met gewassen die beter tegen droogte kunnen, of het plaatsen van airconditioning. Zowel klimaatadaptatie- als klimaatmitigatiemaatregelen brengen kosten met zich mee; er moet dus een afweging plaatsvinden tussen de kosten van klimaatbeleid en het verminderen van klimaatschade door dit beleid. Een groot deel van dit proefschrift gaat precies over deze afweging.

Een belangrijke toepassing van Integrated Assessment Models is het uitrekenen van economisch optimale mondiale temperatuurdoelen en van de social cost of carbon (een indicator voor een optimale prijs die zou moeten worden geheven op de uitstoot van broeikasgassen), of, op zijn minst, om te begrijpen wat de belangrijkste factoren en onzekerheden zijn bij het uitrekenen van deze eenheden. Een economisch optimaal temperatuurdoel kan worden uitgerekend door te kijken op welk punt de extra kosten van klimaatbeleid niet meer opwegen tegen de extra baten van verminderde klimaatschade. Om die reden spelen de inschattingen van de kosten van klimaatbeleid en de kosten van klimaatschade een belangrijke rol. Vooral het inschatten van de economische kosten van klimaatschade is ingewikkeld. Dit heeft gezorgd voor een grote variatie in gepubliceerde kosten-optimale temperatuurdoelen: van 3,1°C met het oorspronkelijke DICE-model in 1992, 3,5°C met de laatste versie van DICE uit 2016, tot aan 1,4°C als er andere aannames worden gemaakt over het klimaat en de economie (Hänsel et al., 2020).

Ondanks de grote hoeveelheid wetenschappelijke publicaties over dit onderwerp zijn een aantal belangrijke aspecten nog onderbelicht in de literatuur. Ten eerste is er nog weinig inzicht in de relevante onzekerheden. Ten tweede worden er bij studies die bepalen hoe klimaatdoelen behaald kunnen worden geen rekening gehouden met klimaatschade; deze studies proberen namelijk alleen de kosten van het klimaatbeleid te minimaliseren zonder rekening te houden met de kosten van klimaatverandering zelf. Ten derde zijn zowel de kosten van klimaatbeleid als de kosten van klimaatschade vaak gebaseerd op oude data die geen goede weergave zijn van de huidige wetenschappelijke kennis op dit gebied. Ten vierde hebben de meeste studies tot nu toe een sterke focus op het minimaliseren van kosten, zonder daarbij expliciet rekening te houden met eerlijkheid en ongelijkheid.

8.2. Doel van dit onderzoek

Nu de discussies en keuzes ten opzichte van klimaatbeleid van steeds groter maatschappelijk belang zijn, is er een duidelijke behoefte aan wetenschappelijke inzichten in de ingewikkelde wisselwerkingen tussen klimaatbeleid en de effecten van klimaatverandering. Dit onderzoek behandelt de verschillende aspecten van kosten-optimaal klimaatbeleid door de volgende onderzoeksvraag te beantwoorden: **"Hoe kan effectief klimaatbeleid worden vormgegeven op basis van kosten-batenanalyse, rekening houdende met de nieuwste wetenschappelijke inzichten in de kosten van klimaatbeleid, de schade van klimaatverandering, en de grote onderliggende onzekerheden?"**

Omdat dit nog steeds een breed onderwerp is, is de onderzoeksvraag opgedeeld in vier sub-onderzoeksvragen:

1. Wat zijn de belangrijkste bronnen van onzekerheid in kosten-batenanalyses van klimaatbeleid?
2. Hoe beïnvloeden nieuwe inzichten over klimaatschade de uitkomsten van kosten-batenanalyses, in het bijzonder het economisch optimale temperatuurdoel?
3. Hoe wordt het kosten-optimale emissiepad beïnvloed door keuzes over negatieve emissies en door onzekerheid in socio-economische ontwikkelingen en bijbehorende mogelijkheden voor adaptatie?
4. Hoe kunnen aspecten van eerlijkheid en welvaart worden gecombineerd met kosten-optimaliteit bij het bepalen van regionale klimaatdoelen?

Dit proefschrift probeert deze onderzoeksvragen te beantwoorden aan de hand van vijf onderzoekshoofdstukken. Dit leidt tot de volgende hoofdresultaten.

8.3. Hoofdresultaten

De onzekerheid in het inschatten van de kosten van klimaatschade heeft een grote impact op optimaal klimaatbeleid, waaronder het optimale doel, de timing van het beleid, en de eerlijke verdeling van regionale klimaatdoelen. De onzekerheid in klimaatschade blijkt de grootste bron van onzekerheid te zijn bij het bepalen van een optimaal temperatuurdoel. Deze onzekerheid wordt veel onderschat in de huidige literatuur. Als de schade van klimaatverandering ook mee wordt genomen bij het bepalen hoe een temperatuurdoel het best bereikt kan worden, leidt dit tot ambitieuzer klimaatbeleid op de korte termijn, zodat er gedurende de komende eeuw al meer schade wordt vermeden. Dit zorgt tegelijkertijd voor minder overshoot: een tijdelijke overschrijding van het temperatuurdoel.

8

Hierdoor is er minder afhankelijkheid van technologieën die koolstofdioxide uit de atmosfeer verwijderen (ook wel aangeduid als negatieve emissies). Als eenmaal is bepaald wanneer de mondiale emissies gereduceerd moeten worden om het doel te bereiken, spelen de impacts van klimaatverandering ook een grote rol in het eerlijk verdelen van de regionale kosten van klimaatbeleid en klimaatschade.

Effectief klimaatbeleid moet rekening houden met belangrijke onzekerheden wanneer kostenbaten-analyses worden gebruikt. Een deel van de onzekerheid kan worden verminderd door normatieve keuzes te maken (zoals de keuze van discontovoet, die aangeeft in welke mate we kosten in de toekomst wegen ten opzichte van huidige kosten). Een andere manier van omgaan met onzekerheid is het maken van beleidskeuzes die expliciet rekening houden met onzekerheid (zoals het voorzorgsprincipe als het gaat om klimaatschade). Effectief klimaatbeleid zal in ieder geval rekening moeten houden met de grote overblijvende bronnen van onzekerheid.

De baten van vermeden klimaatschade wegen ruimschoots op tegen de kosten van klimaatbeleid om ruim onder de 2°C te blijven voor vrijwel alle combinaties van onzekerheden, behalve wanneer de klimaatschade zeer laag blijkt te zijn. In dit proefschrift is de onzekerheid van de kosten en baten systematisch onderzocht. Bij medium of hoge klimaatschade zijn de baten van vermeden schade in 95% van de gevallen hoger dan de kosten van klimaatbeleid om de temperatuurstijging ruim onder de 2°C te houden. De overige 5% zijn veelal scenario's met (zeer) hoge mitigatiekosten. Als de klimaatschade laag uitvalt, zijn de baten slechts in 40% van de gevallen hoger dan de kosten. In dit proefschrift hebben we ook nieuwe inschattingen gemaakt van de klimaatschade, waarbij alle nieuwste inzichten in impacts van klimaatverandering zijn samengevoegd. Ook hierbij blijven de conclusies geldig: voor gemiddelde aannames van schade en discontovoet zijn de baten van klimaatbeleid 1,5 tot 3,9 keer groter dan de kosten. De baten treden echter veelal op in het tweede deel van de eeuw terwijl de mitigatiekosten voornamelijk vroeg in de 21ste eeuw optreden. Als de klimaatschade hoog uitvalt, zijn de baten zelfs 1,8 tot 5 keer hoger dan de kosten.

Dit onderzoek geeft sterke economische argumenten voor het Parijsakkoord. Onder gemiddelde aannames van schade en discontovoet is het kosten-optimale temperatuurdoel ruim onder 2°C, en voor lage discontovoet of hoge schade is het optimale temperatuurdoel zelfs 1,5°C. De conclusie dat het Parijsakkoord ook economisch aantrekkelijk is geldt voor een zeer groot deel van de onzekerheidsrange van de klimaatschade. Bovendien houden de schadefuncties die gebruikt zijn in dit onderzoek geen rekening met aspecten als biodiversiteitsverlies, gezondheidsimpacts, en onvoorziene kantelpunten in het klimaat (tipping points). Daarom is het werkelijke kosten-optimale temperatuurdoel waarschijnlijk nog een stuk lager dan de gemiddelde schattingen. Bovendien zijn er bijkomende voordelen van klimaatbeleid, zoals verminderde luchtvervuiling, waardoor ambitieuze doelen nog aantrekkelijker worden.

Kosten-batenanalyses zijn nuttige tools voor de vormgeving van klimaatbeleid, maar vereisen wel actuele inschattingen van klimaatschade en mitigatiekosten. Verder moeten belangrijke onzekerheden op een transparante manier behandeld worden. Kosten-batenanalyses en de daarvoor gebruikte Integrated Assessment Modellen geven inzicht in de interacties tussen klimaatverandering en beleid. Deze modellen moeten echter wel de laatste wetenschappelijke inzichten gebruiken om beleidsrelevant te blijven.

8.4. Beleidsaanbevelingen

De hoofdresultaten uit dit promotieonderzoek, zoals samengevat in 8.3, leiden tot een aantal beleidsaanbevelingen die hieronder worden besproken.

Ambitieus klimaatbeleid is economisch aantrekkelijk. Dit proefschrift laat zien dat voor ambitieuze klimaatdoelen de baten van vermeden schade substantieel hoger zijn dan de mitigatiekosten. De kosten-optimale temperatuurstijging is dicht bij 1,5°C. De baten in een kosten-optimaal scenario zijn 1,5 tot 3,9 keer hoger dan de kosten van klimaatbeleid (voor gemiddelde aannames van de discontovoet en klimaatschade). Deze baten zouden nog hoger zijn als ontbrekende aspecten mee zouden worden genomen (zoals gezondheidsimpacts, biodiversiteitverlies, en verminderde luchtvervuiling). Het grootste deel van de baten zal echter pas later in de eeuw komen, met een kantelpunt rond 2050 waarin de baten groter worden dan de kosten.

Door de grote onzekerheden in belangrijke aspecten van klimaatbeleid en klimaatschade, is een risico-vermijdende strategie wenselijker dan een gemiddeld kosten-optimaal doel. Hoe groot de schade van klimaatverandering zal zijn is de grootste bron van onzekerheid bij het berekenen van een temperatuurdoel met een kosten-batenanalyse. Het risico dat de schade hoger uitvalt dan gedacht maakt het wenselijker om ambitieuzer klimaatbeleid uit te voeren dan een puur kosten-optimaal klimaatbeleid. De extra mitigatiekosten van te ambitieus klimaatbeleid zijn klein, zeker ten opzichte van de extra klimaatschade als het klimaatbeleid niet ambitieus genoeg is.

De impacts van klimaatverandering zijn niet gelijk verdeeld over de wereld. Het is belangrijk om deze regionale verschillen in klimaatschade ook mee te nemen bij het bepalen van een eerlijke verdeling van mondiaal klimaatbeleid. Momenteel zijn de meeste vormen van mondiale lastenverdeling gebaseerd op mitigatiekosten, terwijl regionale verschillen in klimaatschade daar een grotere rol in zouden moeten spelen.

Welvaart-maximalisering leidt tot strengere beleidsdoelen voor ontwikkelde landen en minder strengere doelen voor ontwikkelingslanden ten opzichte van kosten-minimalisering. Het focussen op welvaart zorgt voor minder ongelijkheid, omdat er hierbij naast mitigatiekosten ook rekening wordt gehouden met regionale verschillen in inkomen en klimaatschade.

Samenvattend hebben we laten zien dat ambitieus klimaatbeleid het economisch meer dan waard is. De instrumenten om emissies te reduceren bestaan, de technologie bestaat. De tijd is gekomen om er nu naar te handelen. Elke stap is belangrijk om de impacts van klimaatverandering te verminderen. Nu iets doen is beter dan morgen, en morgen beter dan overmorgen.

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9.2. List of publications

Published chapters of this thesis:

- **Chapter 2: van der Wijst, K.**, Hof A., van Vuuren, D. On the optimality of 2°C targets and a decomposition of uncertainty. *Nature Communications* **12** 2575 (2021). https://www.nature.com/articles/s41467-021-22826-5
- **Chapter 3: van der Wijst, K.**, Bosello, F., Dasgupta, S. *et al.* New damage curves and multimodel analysis suggest lower optimal temperature. *Nature Climate Change* **13**, 434–441 (2023). https://www.nature.com/articles/s41558-023-01636-1
- **Chapter 4: van der Wijst, K.**, Hof A., van Vuuren, D. Costs of avoiding net negative emissions under a carbon budget. *Environmental Research Letters* **16 6** (2021). https://iopscience.iop.org/article/10.1088/1748-9326/ac03d9

Other scientific publications:

- Hof A.* **van der Wijst, K.***, van Vuuren, D. The Impact of Socio-Economic Inertia and Restrictions on Net-Negative Emissions on Cost-Effective Carbon Price Pathways. *Frontiers in Climate* **3** (2021) (* shared first authorship). https://doi.org/10.3389/fclim.2021.785577
- Kikstra, J., Nicholls, Z., …, **van der Wijst, K.** *et al.* The IPCC Sixth Assessment Report WGIII climate assessment of mitigation pathways: from emissions to global temperatures. Geoscientific Model Development **15-24** (2022). https://doi.org/10.5194/gmd-15-9075-2022
- Chen, H., Hof, A., …, **van der Wijst, K.** *et al.* Using decomposition analysis to determine the main contributing factors to carbon neutrality across sectors. *Energies* **15** 1 (2022) https://doi.org/10.3390/en15010132
- Drouet, L., Bosetti, V., …, **van der Wijst, K.** *et al.* Net zero-emission pathways reduce the physical and economic risks of climate change. *Nature Climate Change* **11** 12 (2021) https://www.nature.com/articles/s41558-021-01218-z
- Gazzotti, P., Emmerling, J., Marangoni, G., Castelletti, A., **van der Wijst, K.**, Hof, A., Tavoni, M. Persistent inequality in economically optimal climate policies. *Nature Communications* **12** 3421 (2021) https://www.nature.com/articles/s41467-021-23613-y
- Harmsen, M., Kriegler, E., van Vuuren, D., **van der Wijst, K.** *et al.* Integrated assessment model diagnostics: key indicators and model evolution. *Environmental Research Letters* **16** 5 (2021) https://iopscience.iop.org/article/10.1088/1748-9326/abf964/
- van den Berg, N., Hof. A, **van der Wijst, K.** *et al.* Decomposition analysis of per capita emissions: a tool for assessing consumption changes and technology changes within scenarios. *Environmental Research Communications* **3** (2021) https://iopscience.iop.org/article/10.1088/2515-7620/abdd99/

9

9.3. Acknowledgements

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Figure 9.1. Working together on new projects.