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

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Abstract

Economic analyses of global climate change have been criticised for their poor representation of climate change damages. Here, we apply newly developed aggregate damage functions in three economic Integrated Assessment Models 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, even with optimal adaptation to sea-level rise, and about 2% in a well-below 2 °C scenario. Using cost-benefit analysis, we conclude that the optimal temperature increase is below 2 °C with central estimates of damages and medium social discount rates with a Benefit-Cost Ratio of 1.5 to 4.0, even without accounting for non-market damages, such as biodiversity losses, and tipping points.

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 related processes and the uncertainties involved. While there is a rich literature on mitigation costs[1–7], it has been notoriously difficult to get reliable information on the benefits. 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[8–12], 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 early CBA, most estimates of damage functions relied on the monetisation of bottom-up sectoral physical impacts, often stemming from semi-qualitative assessment by experts[13–16]. However, very little information on the physical impacts of climate change was available at the time. In recent years, top-down estimates have been developed which relate observed temperature with economic growth[17–19]. 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. This drawback can be partly overcome by applying a “modular” or bottom-up method using the improved estimates of sectoral physical impact modelling[20–22]. These physical damages are translated into economic losses by economic models like, for instance, Computable General Equilibrium (CGE) models[23–25] with improved representation of driving forces and transmission mechanisms of economic impacts.

Recently, a new set of regional climate change damage functions[26] were built in a bottom-up process as part of the European Horizon 2020 project *COACCH* (www.coacch.eu). They are based on CGE model runs analysing the economic consequences of 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) [26]. Compared with similar exercises[24,25,27], these new damage functions 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. 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[28]. Several studies have been published in recent years looking into uncertainty in cost-benefit analysis. These studies typically only consider a single model[28–30] 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[28], and the process-based models WITCH[31] and REMIND[32]. 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. 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. We also calculate Benefit-Cost Ratios (BCRs) for these optimal emission pathways: how much money is saved on avoided damages for every euro spent on climate change mitigation?

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 the emission trajectory of the pre-defined baseline, i.e. Representative Concentration Pathway[33] (RCP) 6.0, and a trajectory in line with the well below 2 °C target of the Paris Agreement, i.e. RCP 2.6. As this means that the same damages are used, this experiment reveals whether the model parameterisations shaping the economic growth and emission processes or their climate modules 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[34,35]. Unless stated otherwise, we assume that optimal adaptation has taken place against sea-level rise damages. Therefore, reported SLR damages are the sum of SLR adaptation costs and residual damages.

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 2.4-3.4% GDP loss in 2100. The economic damages are not very sensitive to the model used.

In Fig. 1, 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[36] to facilitate comparison (see Methods). Moreover, the REMIND IAM does not model sea-level rise explicitly and therefore uses a combined damage function that depends only on temperature.

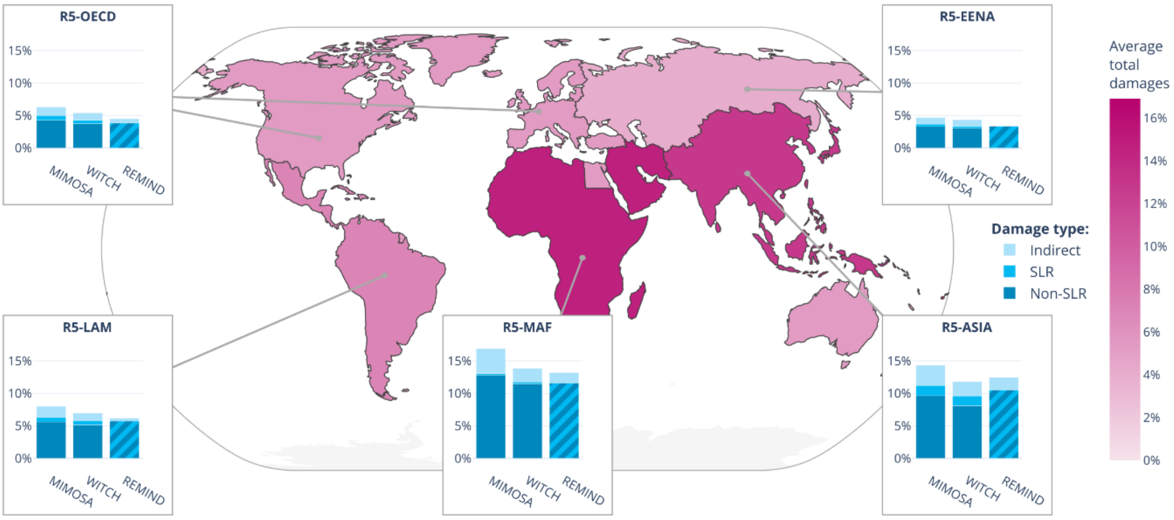
There is high agreement across models also on regional damage patterns, although the ranges are larger in some regions than others. In the RCP 6.0 scenario (Fig. 1a), the damages are the highest in the Middle East and Africa region, with total losses between 13% and 17% of GDP, followed by 12% to 14% for Asia. The other three regions have lower total damages (6-8% for Latin America, 4-6% 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 (12-16% 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 10-12% with SLR adaptation to global damages of 13-17% without SLR adaptation). This is especially pronounced in the OECD (4-6% total damages with SLR adaptation to 8-13% total damages without SLR adaptation).

RCP 2.6 reduces the total damages to a regional maximum of 4.5%, compared to the 15% for RCP 6.0 (Fig. 1b). 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).

In REMIND, total damages with SLR adaptation are similar to MIMOSA and WITCH, despite using the combined damage curves (instead of the separate SLR and non-SLR damage functions). However, larger differences emerge in the RCP 2.6 scenarios without SLR adaptation (Fig. SI.1.1b): the REMIND damages are between 20% and 75% lower than MIMOSA and WITCH, highlighting the importance of separating sea-level rise damages from other temperature-related damages. This effect is shown in more detail in Fig. SI.1.2, where MIMOSA is run with the separate damage functions and the combined damage function to isolate the effect of the different functions.

a. Damages in 2100 (**RCP 6.0,** with SLR adaptation)



b. Damages in 2100 (**RCP 2.6,** with SLR adaptation)

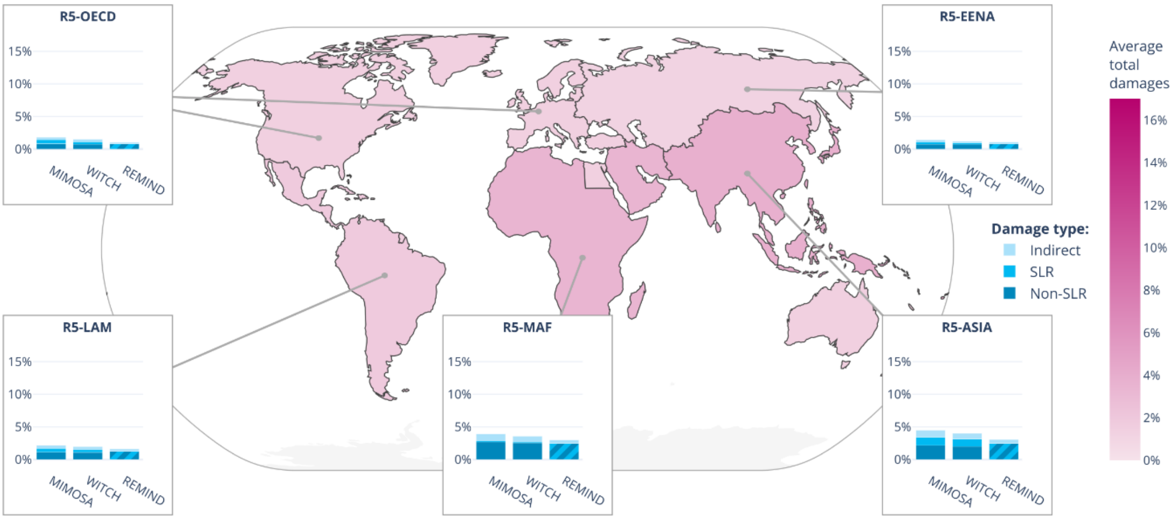


***Figure 1**. Damages in RCP6.0 (a) and RCP2.6 (b) in 2100 for the 5 macro-regions*[*]*. The REMIND model does not model sea level rise explicitly and uses a combined damage function that aggregates both SLR and non-SLR damages.*

Impact of damage curve uncertainty

Above, we concentrated only on 2100 and the 50th damage quantile. Here, we look at how uncertainty in damages impacts the results. Fig. 2 shows that uncertainty in the damage function strongly affects the overall damages. The total damages are significantly higher with the high damage quantile (95th damage quantile, see Methods): 18-22% global average GDP loss instead of 10-12% for the medium damage quantile. The global impacts can even be positive for lower damage quantiles up to 2050 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.

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[37], and, accordingly, losses are lower.

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[*] This figure does not show intra-regional differences; only the population-weighted average per macro-region is shown. For this reason, Egypt, part of the OECD region, looks so different from the surrounding countries, which are part of the Middle East and Africa region.

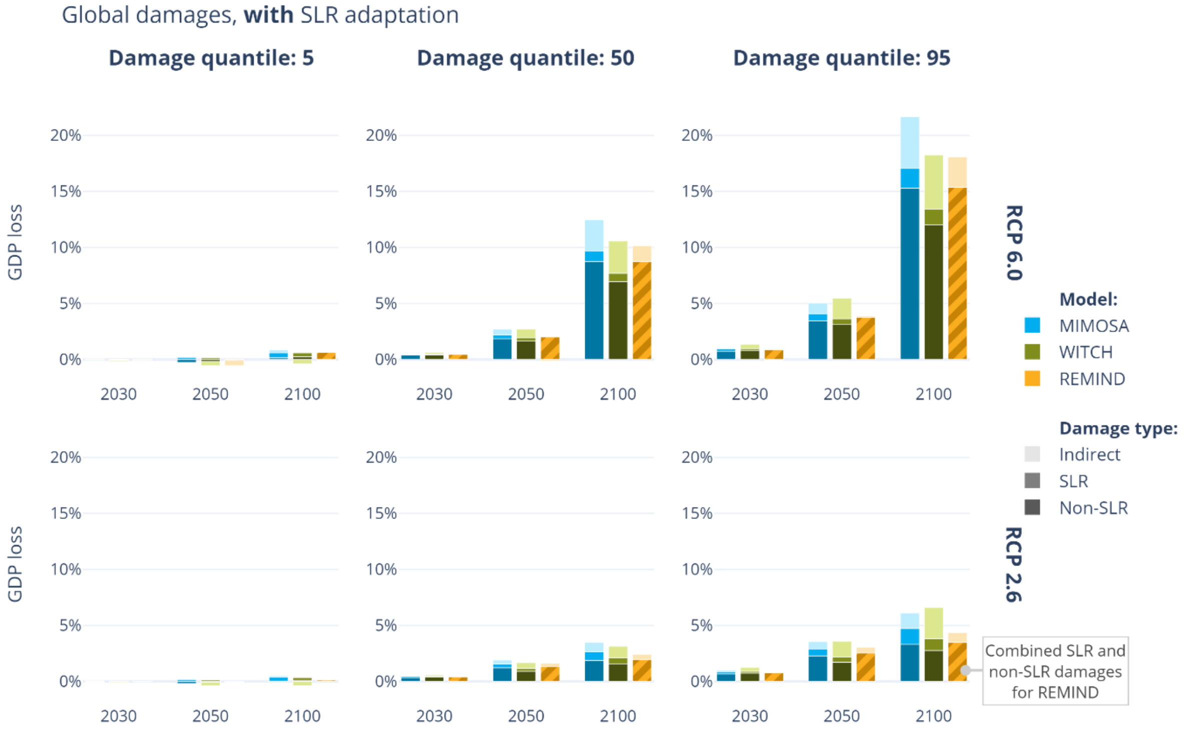


***Figure 2**. Damage cost decomposition of the global GDP losses with optimal sea-level rise adaptation for RCP 6.0 (top row) and RCP 2.6 (bottom row) for three levels of damages (low: 5th quantile, medium: 50th quantile, high: 95th quantile). Note that REMIND does not model sea level rise explicitly.*

Cost-benefit analysis

We now add mitigation costs of each model to perform a comprehensive CBA. We consider first the role of damage uncertainty and then that of discounting economic losses.

Damage uncertainty

The cost-benefit results are presented in Fig. 3. The cost-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[‡]. 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[28,38,39] 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.

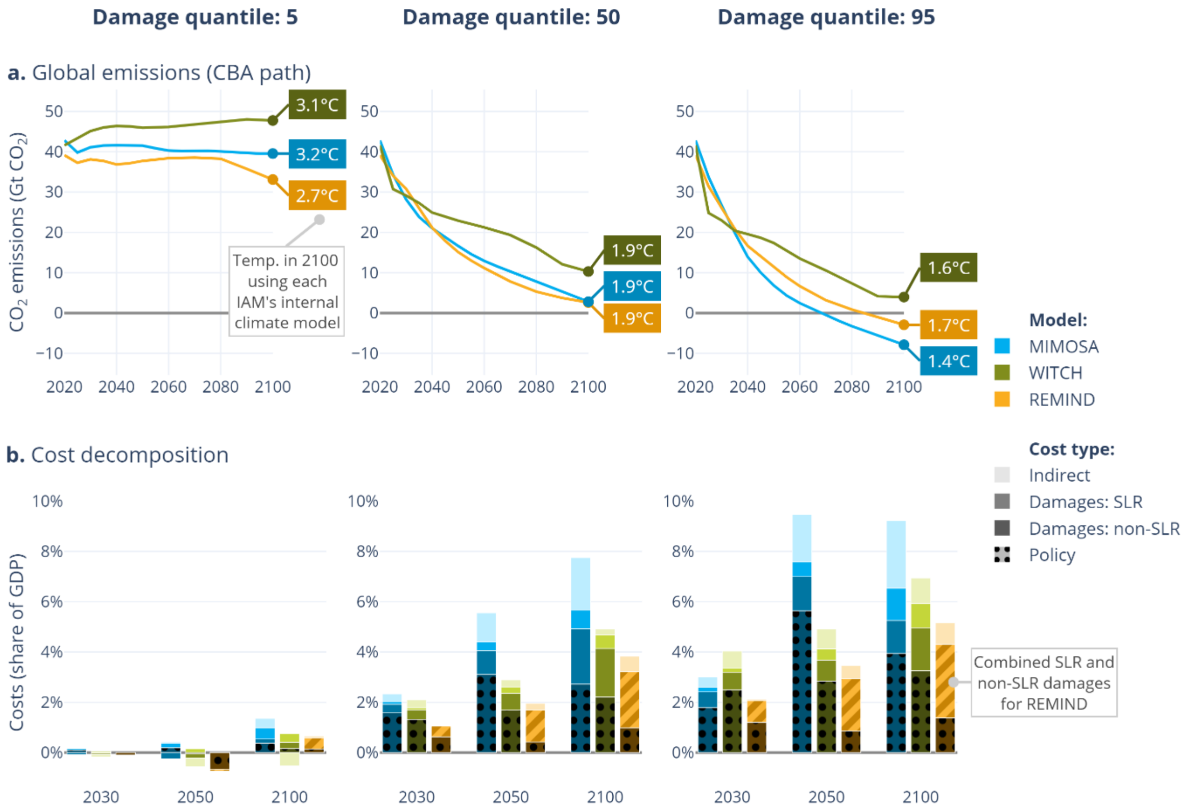
As expected, the low damage function leads to higher optimal end-of-century temperature increases of 2.7-3.2°C, and the higher end of the damages leads to optimal temperature increases, which are very close to the 1.5 °C target of the Paris Agreement (1.4-1.7°C).

[†] Note that all models actually maximize welfare, thus in a strict sense all results are welfare-optimal.

[‡] Note that these temperature estimates are median climate estimates; we have not assessed uncertainty in the climate module.

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. 3b, see also [6]). 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 3% of GDP for the medium CBA scenario), but the model is more flexible in achieving higher mitigation levels. It has less strict inertia constraints and allows far 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 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 CO2 emissions, other greenhouse gases, and the climate model used.



Temp. in 2100 using each IAM's internal climate model

Combined SLR and non-SLR damages for REMIND

***Figure 3**. (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). (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.*

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[28,29] and a recent expert elicitation[40]. 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[41] 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[42], while keeping the elasticity of marginal utility fixed.

As shown in Fig. 4, 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 over 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.

Figure 4*. The optimal end-of-century temperature 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. Note that REMIND has not been calibrated to use the low utility discount rate.*

Comparing costs to avoided damages: 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 benefits of mitigation. Comparing the total discounted avoided damages to the total mitigation costs gives a Benefit-Cost Ratio. Globally, 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. Since these scenarios are performed in a cooperative setting, only the global results are relevant. 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 4.0, Fig. 5). This gives strong economic validation of the Paris-consistent mitigation scenario. When assuming the high damage function, the benefit-cost ratio increases to 1.8 - 5.1 for medium discounting (Figure SI.2.2.). Since the low damage function yields CBA paths with very low to no mitigation effort, the BCR cannot be calculated here.

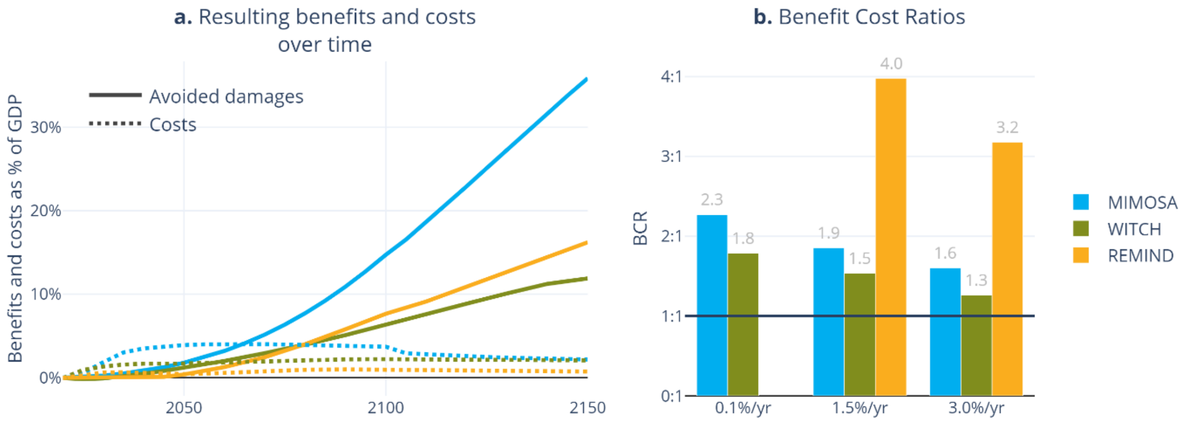


***Figure 5**. Benefit-cost ratio for the CBA scenario using the medium damage function (50th percentile). Left: policy costs (dotted lines) and avoided damages (benefits, solid lines) over time for the scenario with medium discounting. Right: Benefit-Cost Ratio (BCR): total discounted avoided damages divided by the total discounted mitigation costs. Note that REMIND is not calibrated for the lowest discount rate.*

Discussion

Our 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 in line with the well below 2°C target from the Paris Agreement 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 impacts like biodiversity loss, health impacts and socio-economic and geophysical tipping points, the resulting temperature outcomes are likely to be conservative. On the other hand, the current COACCH damage functions only explicitly modelled adaptation for sea-level rise. For the other impacts, adaptation is implicitly addressed in the CGE, but not in the impact models, since some level of “market driven adaptation” occurs in the CGE optimisation process, where economic assets can be reallocated between sectors and regions. 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[13], Howard et al. [43] and Burke et al. [17] functions (see Fig. Methods.1.), thus also leading to similar optimal temperature levels[22]. 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[13], FUND[14] and PAGE[15]) are the lack of empirical foundation, the relatively simple monetisation method used, and that they are based on relatively old and scare impact data[44,45]. On the other hand, 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[46,47]. 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 1).

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[48–51], 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.

This analysis highlights the importance of including the full range of damage function uncertainty, as this strongly impacts 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.

Methods

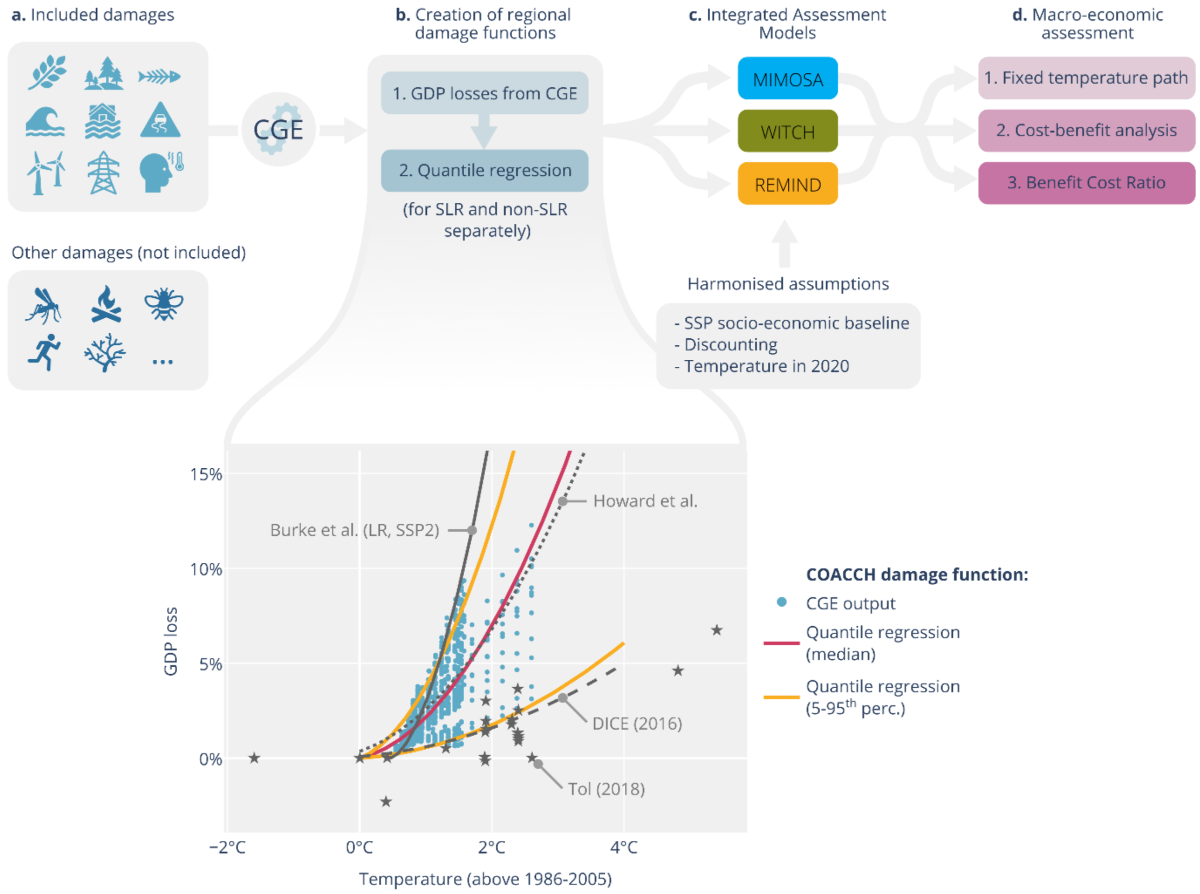


Figure Methods.1*. Overview of the creation and use of the damage functions. Results from 9 sectoral impact models are included in a CGE model to calculate GDP losses for various scenarios and points in time. Using quantile regression, a curve is fitted through the points at the 5th percentile (low estimate), 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.*

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 models have been evaluated in their macroeconomic consequences applying the ICES recursive-dynamic computable general equilibrium model[52] (www.icesmodel.org). The list of impacts considered and their implementation in the CGE model for the evaluation are reported in 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[53]. 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.

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

Climate change impact area	Impact model sourcing data	Variable	Modelling implementation for the economic assessment
Agriculture	EPIC biophysical model[54] and GLOBIOM model[55], updated in 2021	(Change in) Crop yield	Changes in the productivity of the "land input" to the regional agricultural sectors
Forestry	G4M model[56]	(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[57] and DSFM food web model[58]	(Change in) Fish catches	Changes in the productivity of the "natural resource" input to the regional fish industries
Sea-level rise	DIVA model[59]	- 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[60]	- 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[61]	- 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)[62]	- Changes in wind and hydropower production	- Change in the total factor productivity of the regional wind and hydro energy sector
Energy Demand	Schleypen et al., (2019)[62]	- 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
Heat stress on the labour force	Schleypen et al., (2019)[62]	- Changes in per capita production of value added	- Changes in regional labour productivity

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[35]. 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 (Fig. 7).

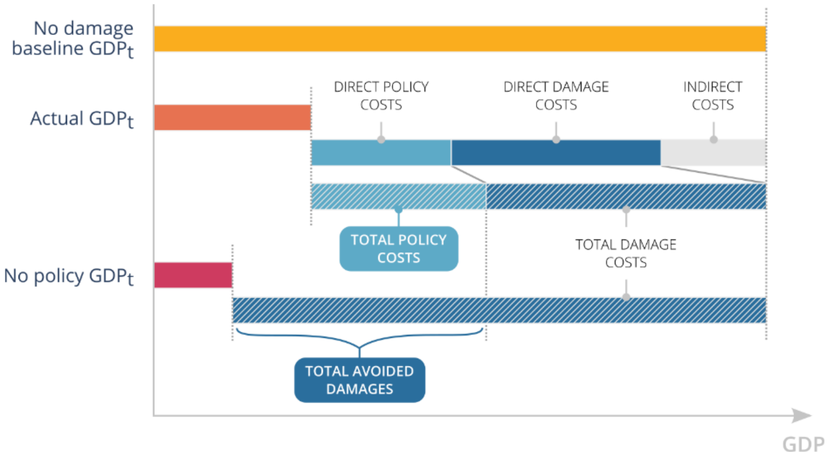


Figure Methods 2. *Calculation of the costs and the benefits (avoided damages) for the Benefit-Cost-Ratio analysis. First, the direct policy and residual damage costs are scaled to include the indirect costs (remaining difference with a baseline run without damages). The scaled residual damages are subtracted from the total damages from a no-policy run.*

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[28] is a recent IAM based on FAIR[63], 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 CO2 emissions. 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 CO2 emissions (see SI.4 for more details).

WITCH[31] 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)[64].

REMIND[32] is an optimal growth IAM with the highest level of detail in the representation of the economy and the energy sector including mitigation options of the three models. However, in contrast with MIMOSA and WITCH, REMIND does not model sea-level rise explicitly, and therefore uses a combined damage function that depends only on temperature.[††] REMIND is soft-coupled to MAGICC[65] as its climate module.

The Computable General Equilibrium model

ICES[66] is a recursive dynamic computable general equilibrium model for the world economy based on the GTAP 8 database[67]. 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.

Harmonisation

To allow a comparison of the results between the models, we harmonise key assumptions. We use the SSP2[68] 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[40] 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

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[§] See https://github.com/kvanderwijst/Project-MIMOSA/ for the model code and documentation.
[**] See https://www.witchmodel.org/ for the model code and documentation.
[††] See https://rse.pik-potsdam.de/doc/remind/2.1.0/ for the model documentation and https://github.com/remindmodel/remind for the model code.

and equal to 1.16°C above pre-industrial levels[69]. 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[36] (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, except Egypt
- OECD: includes all OECD and EU countries except 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[70]. This includes the sea-level rise, non-sea-level rise and combined damage functions for all used damage quantiles.

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