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New damage curves and multimodel analysis suggest lower optimal temperature

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Economic analyses of global climate change have been criticized 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.

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[1–7], it has been notoriously difficult to get reliable information on damages. Similarly, much less is known about the role of the type of Integrated Assessment Model (IAM) used to analyse the costs and benefits. While model intercomparison studies are common for other climate change research areas (https://www.navigate-h2020.eu/, https://emf.stanford.edu/projects/emf-33-bio-energy-and-land-use, https://www.engage-climate.org/, https://www.reinvent-project.eu/, http://www.cd-links.org/), 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 that relate observed temperature with economic growth have been developed[8–10]. 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 assessments by experts, these assessments currently being considered as mostly outdated[11–18].

To overcome these drawbacks, a new set of regional climate change damage functions[12] was recently built in a bottom-up process as part of the European Horizon 2020 project COACCH (www.coacch.eu). These

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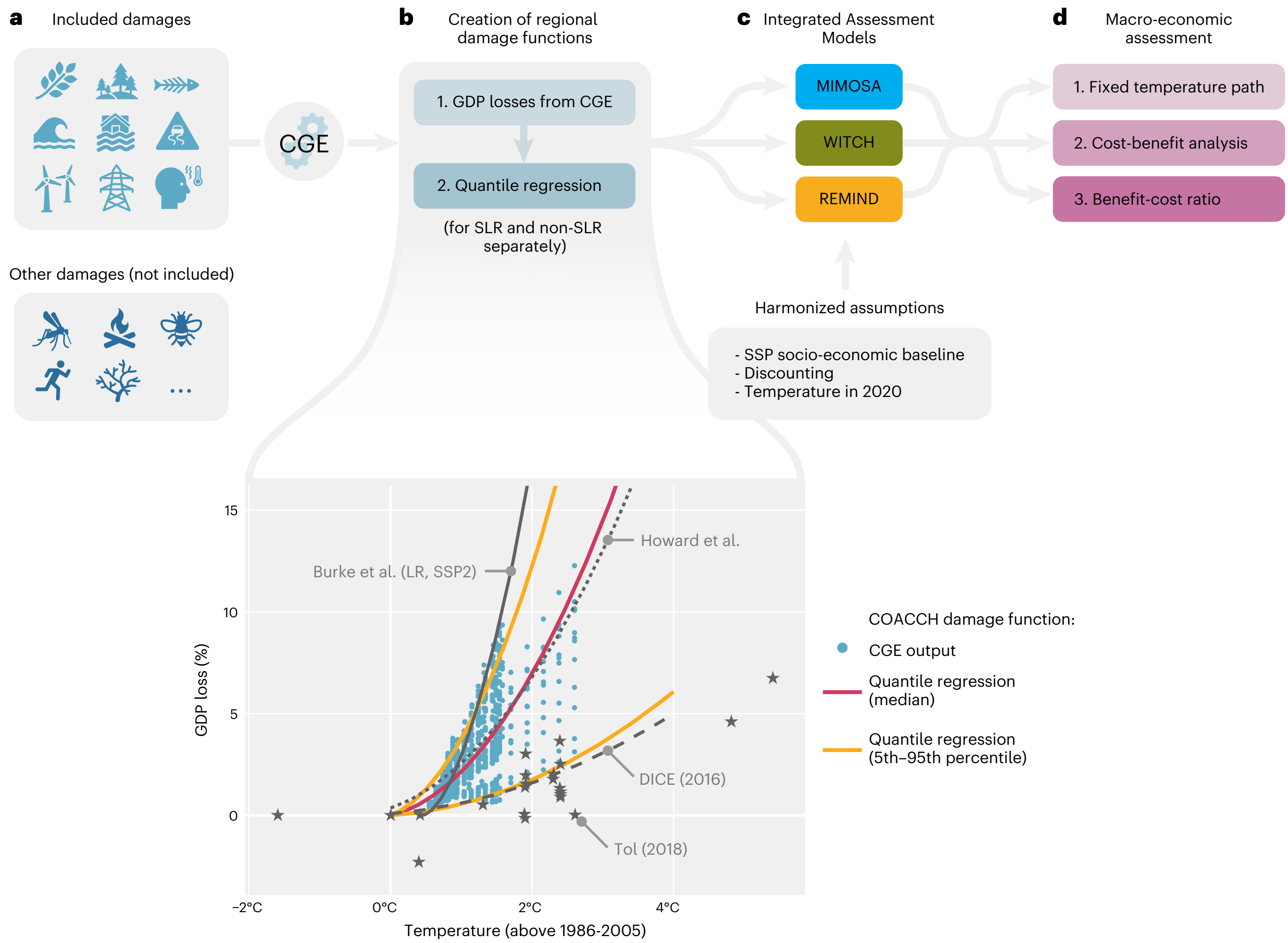

Fig. 1 | Overview of the creation and use of the damage functions. Results from nine sectoral impact models (**a**) are included in a CGE model to calculate GDP losses for various scenarios and points in time (**b**). Using quantile regression, a curve is fitted through the points at the 5th (low estimate), 50th (medium) and 95th (high) percentiles for each region. These reduced-form damage functions are used in the IAMs (**c**) for the macro-economic analysis of this paper (**d**). 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. Burke et al. (LR, SSP2) refers to the SSP2 Long Run damage function.

functions 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)[12]. The impact of these physical damages on economic losses was estimated by an economic model—the Computable General Equilibrium (CGE) model[13–15] ICES[16]—with improved representation of driving forces and transmission mechanisms of economic impacts (Fig. 1 and Extended Data Table 1).

Compared with similar exercises[14,15,17], 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 European Union (EU), where the macro-economic impact assessments are determined at the NUTS2 level. The consistency in uncertainty representation derives from accounting for (1) different climate scenarios, (2) different socio-economic scenarios, (3) different impact ranges within each climate scenario originated by impact model uncertainty and (4) 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 (Methods).

Literature shows that the results of cost-benefit studies depend not only on the damage function but also on the macro-economic parameters and assumptions such as discounting or savings, as well as the representation of mitigation costs and dynamics[18]. Several studies have been published in recent years looking into uncertainty in cost-benefit analysis. These studies typically only consider a single model[18–21] and use the older top-down or empirical damage functions. Here we perform a multimodel CBA study using the newly developed COACCH damage functions, allowing exploration of 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[18], and the process-based models WITCH[22] and REMIND[23]. 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 (hence covering the uncertainty as a 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, this ratio indicating the relationship between the relative costs and benefits of climate mitigation.

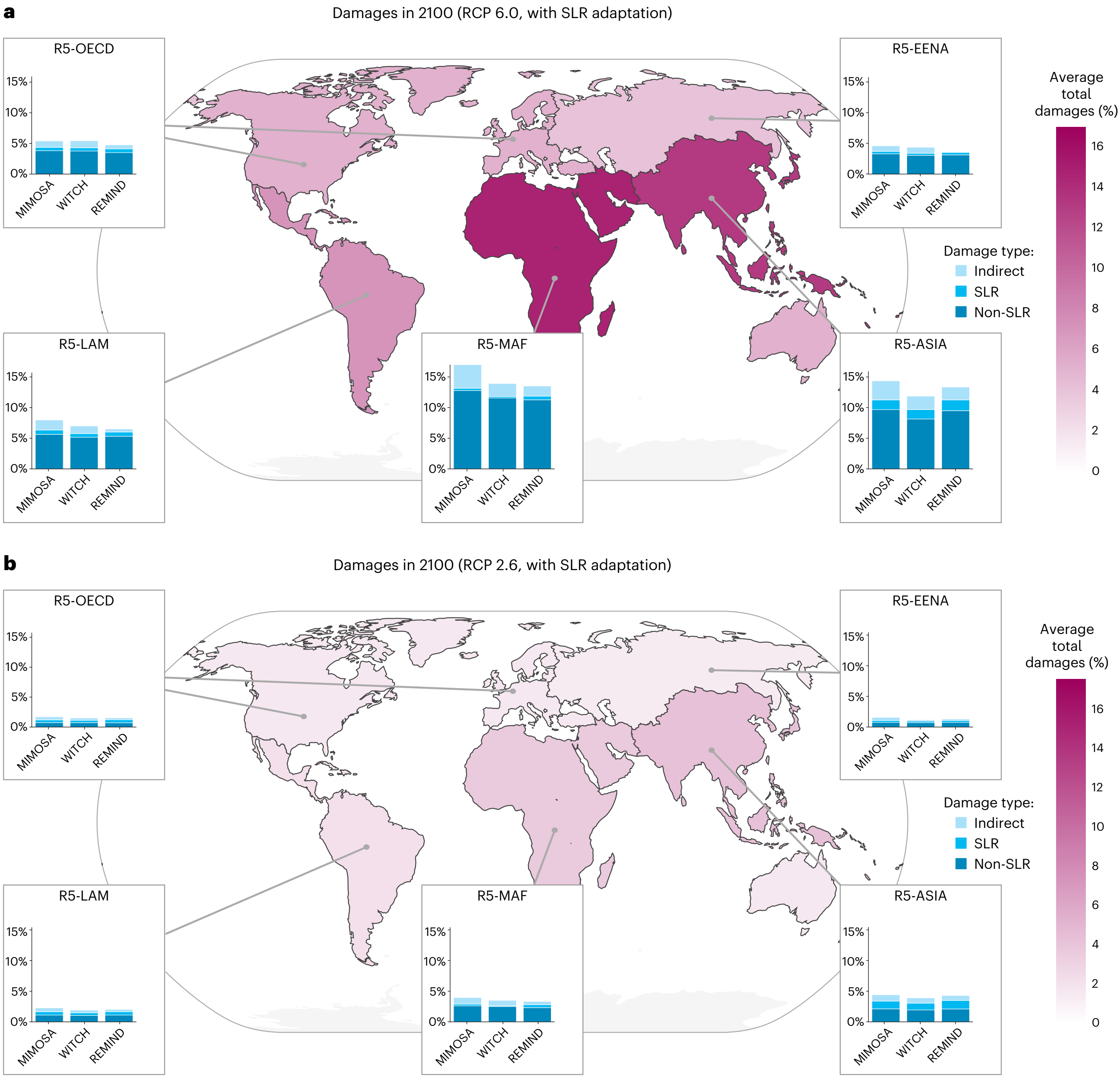

Fig. 2 | End-of-century damages for the five macro-regions for two scenarios. The damages are split into three types (direct temperature-related damages, direct sea-level-rise damages and indirect damages from GDP loss accumulation). The damages are shown for the year 2100 in the RCP6.0 scenario (**a**) and the RCP2.6 scenario (**b**). 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.

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 substantially outweigh the costs of climate policy.

Multimodel 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[24] (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 RCP2.6, which is a trajectory in line with the well-below 2 °C target of the Paris Agreement. We fixed the temperature pathways to reveal whether the model parameterizations shaping economic growth differ substantively.

The COACCH functions allow decomposing the total GDP losses into (1) direct impacts from sea-level rise, (2) direct temperature-related impacts and (3) indirect impacts from cumulated dynamic effects, for example, through investment[25,26]. Unless stated otherwise, we assume that optimal adaptation has taken place against sea-level-rise

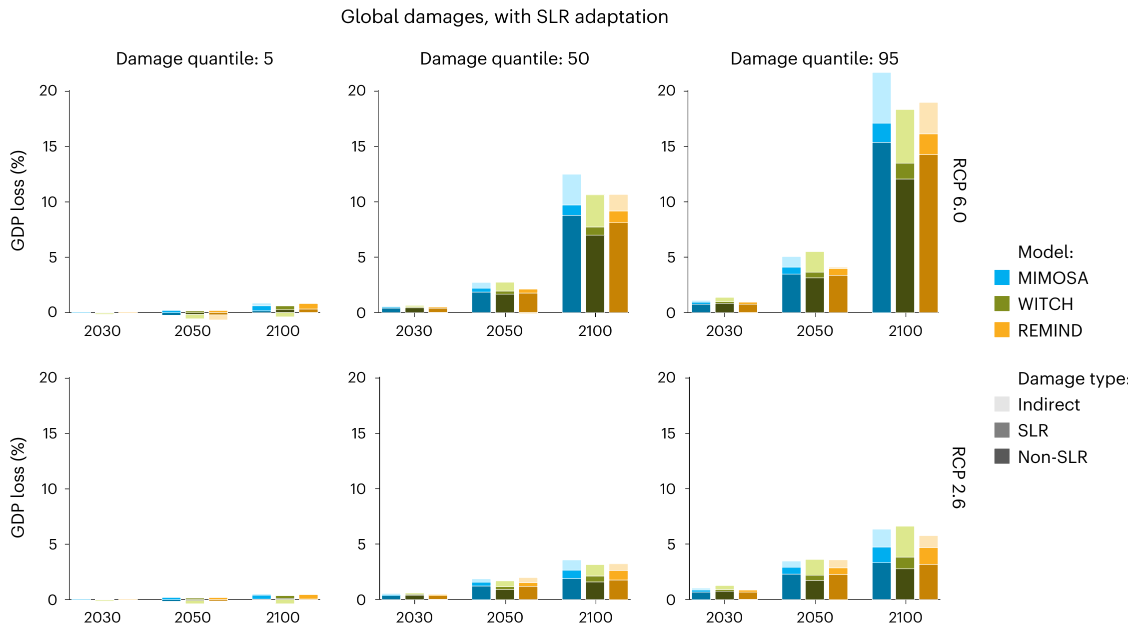

Fig. 3 | Sensitivity analysis of the global damage costs. Damage cost decomposition of the global GDP losses with optimal sea-level-rise adaptation for RCP6.0 (top row) and RCP2.6 (bottom row) for three levels of damages (low: 5th quantile, medium: 50th quantile, high: 95th quantile), in 2030, 2050 and 2100.

(SLR) 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 RCP6.0 scenario ranges from 10 to 12% at the end of the century when using medium damage (50th damage quantile) estimates. The damages are reduced to 3.1–3.6% GDP loss in 2100 in the mitigation scenario RCP2.6. 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 Shared Socio-economic Pathways (SSP) database[27] to facilitate comparison (Methods).

There is high agreement across models also on regional damage patterns, although the ranges are larger in some regions than in others. In the RCP6.0 scenario (Fig. 2a), the damages are 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 Organisation for Economic Co-operation and Development (OECD) (see Methods) and 3–5% for Eastern Europe and Northern Asia (EENA)). 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 substantial 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 (Supplementary Fig. 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[28].

RCP2.6 reduces the total damages to a regional maximum of 4.5%, compared with the 18% for RCP6.0 (Fig. 2b). The regional distribution of damages is similar to RCP6.0, 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 RCP2.6 and RCP6.0 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, such as Asia and the OECD. Without SLR adaptation, Asia and the OECD have the highest damages in RCP2.6 as, in this case, sea-level-rise damages account for most of the total damages (Supplementary Fig. 1.1b).

Impact of damage curve uncertainty

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

Until 2050, the differences between RCP2.6 and 6.0 are still moderate. They only strongly diverge towards 2100 (up to 50% higher damages for RCP6.0 than for RCP2.6 in 2050, whereas the damages are 300% higher towards the end of the century).

REMIND shows lower indirect effects than the other models. While all economic assets are fixed in MIMOSA and WITCH, in REMIND, assets can be relocated, facilitated by more advanced trade mechanisms[29]; accordingly, losses are lower.

CBA

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 (minimizing damages and mitigation costs) instead of cost-effectiveness mode (minimizing mitigation costs only). Previous research[18,30,31] 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.

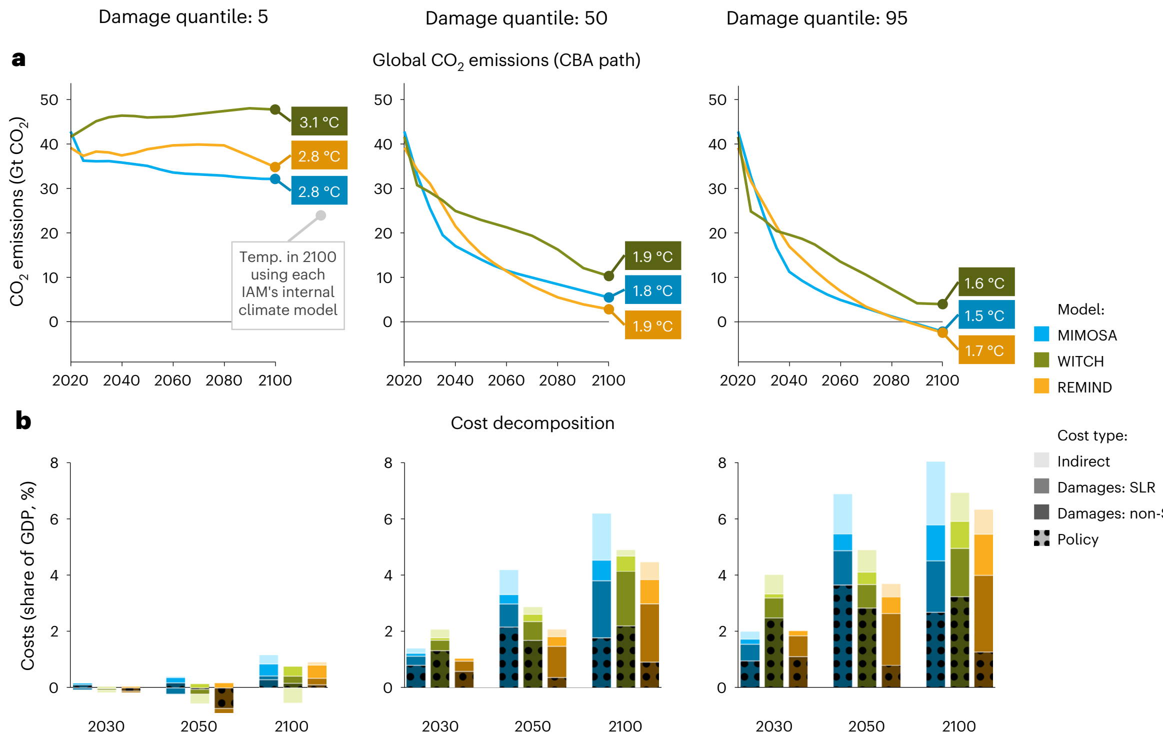

Fig. 4 | Emission pathways, damage costs and climate policy costs in CBA setting. **a**, Cost-optimal emission trajectory and corresponding end-of-century temperature in cost-benefit runs for the low, medium and high end of the damage function uncertainty range (damage quantiles). While only global CO_2 emissions are shown in this figure, each model also takes into account non-CO_2 gases in their calculation of temperature outcomes. **b**, GDP loss (compared to baseline GDP) decomposed into policy costs (mitigation costs), damage costs and indirect costs. Here, the indirect costs result from accumulated GDP impacts from mitigation and damage costs.

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).

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 also be noted that overall mitigation costs are lower in REMIND (Fig. 4b, see also ref. [6]). Nonetheless, in terms of temperature, the model shows the smallest difference (only 0.2 °C) between the 50th and 95th damage quantiles. 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 in 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, becoming less towards the end of the period even with the modest global carbon price of US$67 per tCO_2 in 2030 (Supplementary Fig. 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.

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% yr^{-1}, combined with an elasticity of marginal utility of 1, in line with recent literature[18,19] and a recent expert elicitation[32]. 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% yr^{-1} as a low PRTP value, as in the Stern[33] review, and 3% yr^{-1} as a high PRTP value covering a range similar to the Inter-Agency Working Group on the Social Cost of Carbon[34], 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 across all discounting scenarios is 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. Peak temperatures are in some cases more than 0.1 °C higher than 2100 temperatures, but only for end-of-century temperatures of 1.5 °C or lower (Supplementary Fig. 2.2).

Comparing costs to avoided damages using the BCR

Besides providing a cost-optimal target, an important and policy-relevant metric is the BCR, 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, 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 BCR of mitigation (Extended Data Fig. 1). 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

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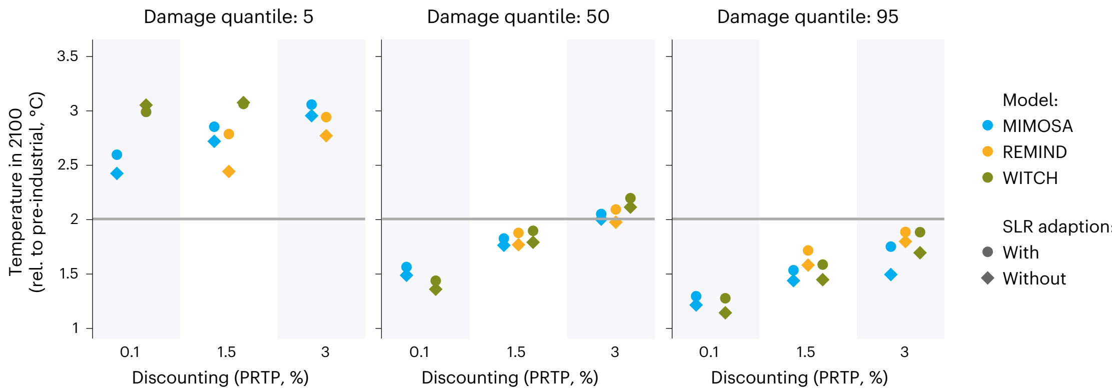

Fig. 5 | Optimal temperature in 2100 in CBA for different levels of discounting and SLR adaptation assumptions. The levels of discounting are quantified by three values of the PRTP, also called utility discounting. REMIND has not been calibrated to use the low utility discount rate.

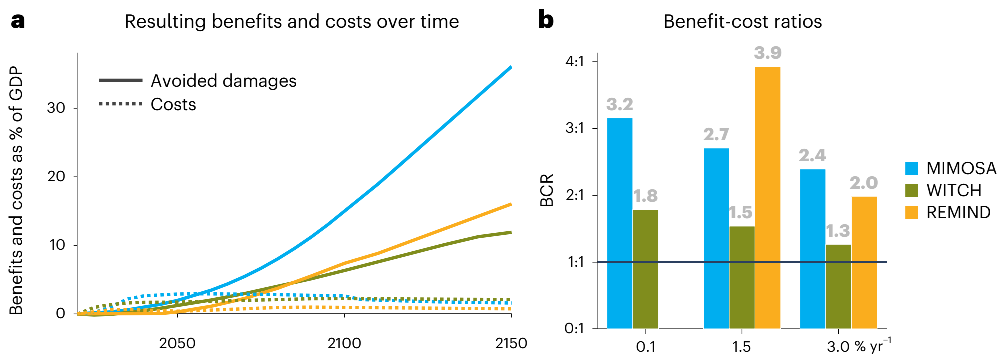

Fig. 6 | BCR for the CBA scenario using the medium damage function (50th percentile). a, Policy costs (dotted lines) and avoided damages (benefits, solid lines) over time for the scenario with medium discounting. **b**, BCR: total discounted avoided damages divided by the total discounted mitigation costs. REMIND is not calibrated for the lowest discount rate. The numbers above the bars correspond to the exact value of the benefit-cost ratio.

2020–2150 time range. Using a medium discount rate (PRTP of 1.5% yr^{-1}), the benefits are almost twice the total discounted costs (multimodel range of 1.5–3.9, 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 BCR increases to 1.8–5.0 for medium discounting (Supplementary Fig. 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).

Discussion

The results in this study show that, from a purely economic perspective, the benefits of reduced climate damages substantially 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 (1) detailed process-based biophysical impacts, (2) a consistent economic modelling approach to quantify and monetize these impacts in a multimodel context, (3) the separation of temperature and sea-level-rise impacts and (4) 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 (for example, 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 the DICE[35], Howard et al.[11] and Burke et al.[8] functions, respectively (Fig. 1), thus also leading to similar optimal temperature levels[17]. 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[35], FUND[36] and PAGE[37]) are the lack of empirical foundation, the relatively simple monetization method used, and the relatively old and scarce impact data they are based on[38,39]. A more recent study[21] 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 such as DICE and Rennert et al.[21], empirical damage functions, such as 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[40,41]. With the advancement of sectoral physical impact models, the COACCH damage functions rely much less on semi-qualitative expert assessment and avoid simple monetization 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 economic assessment (Supplementary Table 3.1). However, more research should be performed to monetize and include more climate impact sectors, such as 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[42–45], this research shows that financing loss and damages are just as important, since even Paris-compliant scenarios still yield substantial 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 BCRs 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, such as burden sharing regimes and emission trading schemes[42,46], 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[18]. 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 can 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 (Supplementary Information 3.2c). These functions include the aggregated effect of SLR and non-SLR damages. They result in similar damages for high-temperature scenarios (RCP6.0, Supplementary Fig. 1.2). However, the combined damages are up to 50% lower than the disaggregated damage functions in an RCP2.6 scenario without SLR adaptation (Supplementary Fig. 1.2), due to the different timescales 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 the three models in the cost-optimal end-of-century temperature is much smaller than the damage and discounting uncertainty, the model range in the BCR does show the importance of including multiple models in a cost-benefit analysis.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-023-01636-1.

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Methods

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 were evaluated in their macro-economic consequences, applying the ICES recursive-dynamic CGE model[16] (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 (refs. [47–56]). The climate change impacts did not include potential losses originated in ecosystems or in the health sector. This is motivated by the difficulty in addressing the non-market dimension of those impacts with a 'market-transaction-based' model such as CGE. Also, catastrophic events were not considered, even though some 'extremes' (riverine floods) were included.

To provide the amplest account for uncertainty, all the impacts were specified for nine combinations of climate change scenarios (RCPs), social economic development scenarios (SSPs) (Supplementary Fig. 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 were used to extrapolate the reduced-form climate change damage functions. Two different types of damage function were estimated using linear and quadratic quantile regression, depending on the region (Supplementary Information 3.1): one specific to sea-level rise, the other to the remaining climate change damages. SLR damage functions were estimated assuming 'current level adaptation' and 'incremental adaptation', when coastal protection is upgraded following the prescription of 'optimal' adaptation from the DIVA model[57]. For the remaining damages, adaptation was 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 Supplementary Information 3.1. The damage functions were estimated through different 'damage quantiles'. Unless otherwise stated, the medium damage estimate is the 50th quantile, and the low and high estimates are the 5th and 95th quantiles, respectively.

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[26] 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 calculated 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 obtained the indirect damages. For the CBA runs, it was not possible to distinguish between reduced economic growth from climate impacts and from mitigation costs. We therefore did not report the 'indirect damages', but instead report the 'combined indirect costs' from both damages and policy costs. These were calculated as the difference 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 obtained the combined indirect costs. For the BCR calculation, the indirect costs need to be included for a fair comparison of benefits and costs. We therefore scaled the direct policy and residual damage costs to include the indirect costs to obtain total policy and residual damage costs. The residual damages were then subtracted from the total damages in a no-policy scenario (Extended Data Fig. 1).

IAMs

To assess the macro-economic implications of the new COACCH damage functions, we used 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[18] is a recent IAM based on FAIR[58], 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[59]. 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 Supplementary Information 4 for more details). The direct regional mitigation costs are calculated as area under the marginal abatement cost curve and have been recalibrated to the IPCC AR6 WGIII database.

WITCH[22] is a dynamic optimization 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.[60]. Mitigation costs are endogenously computed on the basis of a fully hard-linked energy system covering all main energy supply technologies and demand sectors. Moreover, land-use mitigation actions and costs are computed on the basis of the linked GLOBIOM model. The policy costs are then calculated as total GDP loss compared to a baseline scenario without climate policy.

REMIND[23] 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[61] as its climate module. The policy costs are calculated as GDP losses compared to a baseline scenario without climate policy.

The CGE model

ICES[16] is a recursive-dynamic CGE model for the world economy based on the GTAP8 database[62]. While GTAP10 was available at the time of writing, ICES has been calibrated separately for the entire 2020–2070 period according to the macro-economic 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 was developed featuring a sub-national resolution for the EU economies represented by 138 territorial units. We considered 24 different economic sectors. An extended description of the ICES model and of the calibration process is provided in Supplementary Information 6. Using a CGE to calculate the damages allows the use of the highly detailed representation of the economy to account for feedbacks and rebound effects triggered by climate change impacts.

Harmonization

To allow a comparison of the results between the models, we harmonized key assumptions. We used the SSP2[27] assumptions on baseline GDP, population growth and baseline emissions. The discounting was also harmonized: by default, we used a PRTP (also called utility discount factor) of 1.5% yr^{-1} and an elasticity of marginal utility of 1.001, in line with a recent expert elicitation[32] on discount rates. Since temperature is an essential factor determining the climate damages, the climate models were calibrated such that the 2020 temperature was harmonized and equalled to 1.16 °C above pre-industrial levels[63]. 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 assumed 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 aggregated all results to the five macroregions of the SSP database[27] (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 were harmonized 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 are available at https://doi.org/10.5281/zenodo.7627679. Source data are provided with this paper.

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 are 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. F.B., R.P., G.S., S.D. and K.-I.v.d.W. developed the damage functions. F.B., L.D., J.E., A.H., M.L., F.P., D.v.V. and K.-I.v.d.W. developed and ran the CBA scenarios. K.-I.v.d.W. performed the multimodel analysis.

Competing interests
The authors declare no competing interests.

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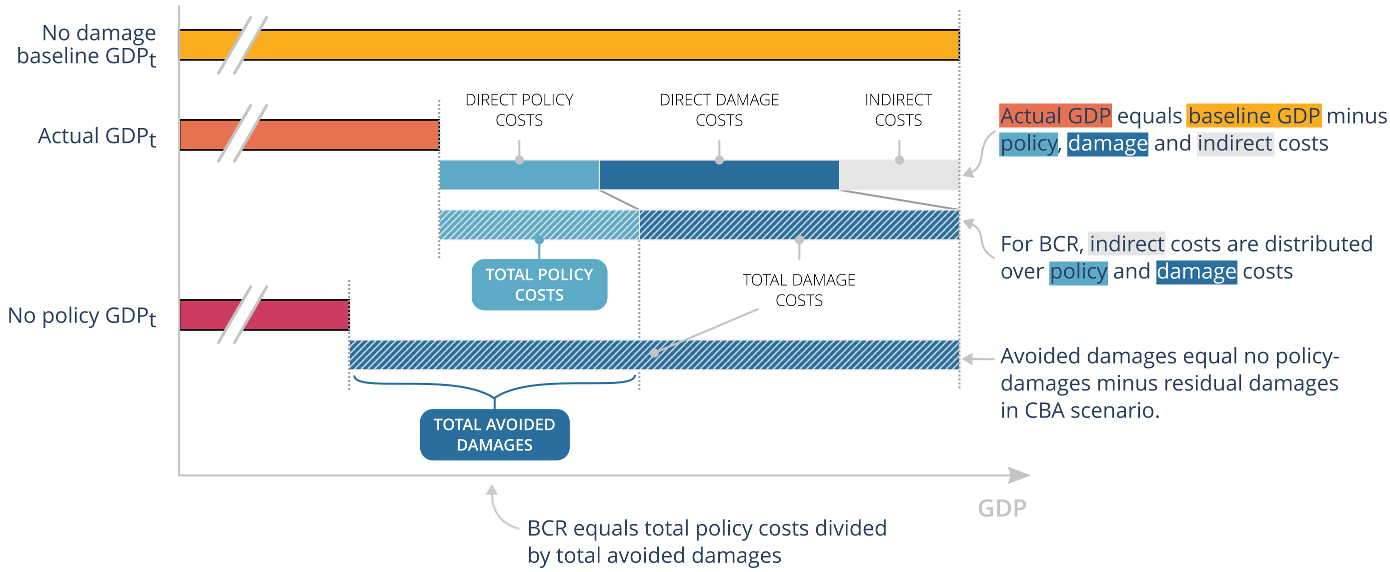

Extended Data Fig. 1 | Calculation of the costs and the benefits (avoided damages) for the Benefit-Cost-Ratio analysis. First, the direct policy and residual damage costs are scaled to include the indirect costs (remaining difference with a baseline run without damages). The scaled residual damages are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

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Extended Data 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[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