CHIPS
Climate Change Impacts and Policies in Heterogeneous Societies

Deliverable 2.2: Report on the long-term growth effects of different types of climate hazards and their interplay with climate policy targets

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The long-term growth effects of different types of climate hazards and their interplay with climate policy targets

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1. Introduction

Climate change impacts and their economic effects are the key motivation for climate policy. They are being felt already today, in particular through increasing strength and frequency of extreme events like floods, droughts or storms (O'Neill et al. 2022). Furthermore, they affect inequality as they likely have a larger effect on the poor (e.g. Hallegatte & Rozenberg 2017).

However, their quantification and representation in economic models, in particular also integrated assessment models (IAMs) used to examine climate policy and transformation strategies and pathways, remains a challenge. Reasons include the multitude of channels through which damages affect socioeconomic systems, the high level of temporal and spatial aggregation typical for integrated assessment models and the disconnect between the biophysical and economic research communities. Therefore, improvements both in the representation in IAMs and in the quantification and understanding of economic damages are a key prerequisite to model their distributional effects. The CHIPS project contributes to that in a number of different ways: (i) by assessing the state of the literature and contributing to the overall research agenda setting; (ii) by focusing on different types of impacts and their economic valuation; and (iii) by improving the representation of impacts in the IAMs. This report collects key results from these efforts and is organized along these three lines of research. The first part reports on a number of review and perspective studies, the second part summarizes key contributions on different types of damages (labor, tropical cyclones, droughts, floods). For these parts, more details can be found in the papers themselves. Section 3 presents implementations in the REMIND IAM and some results. The final part discusses linkages to the other work packages in CHIPS and avenues for future research.

2. Assessing and advancing the state-of-the art of economic damage estimates

The following section starts out by discussing two perspective papers aiming to summarize the state of the art and outlining gaps and a future research agenda regarding the assessment of economic impacts of climate change. An additional paper from the CHIPS project not discussed in detail due to space constraints is a review paper on the state of the art of knowledge on impacts in the energy sector, including both energy supply and energy demand (Yalew et al. 2020). The second part of this section focuses on new economic impact quantifications valid for application in global models. A study in preparation focusing on vulnerabilities of the Texas power grid to hurricane-induced cascading failures (Stürmer et al., in prep.) is not discussed as it has a very local focus.

2.1. From biophysical to economic impacts (Piontek et al. 2021, Rising et al. 2022)

Piontek et al. (2021) provide a comprehensive overview of the current state of the art and the challenges around the translation of biophysical climate change impacts into economic damages, focusing on the global level with the aim of using the damages in integrated assessment. Starting from a taxonomy of the different approaches used for this translation (Figure 1), they discuss in detail four ways to quantify economic damages: a bottom-up assessment of direct economic impacts, an assessment of final economic impacts which includes feedback effects and can be undertaken both top-down and bottom-up, and the derivation and use of aggregate damage functions.

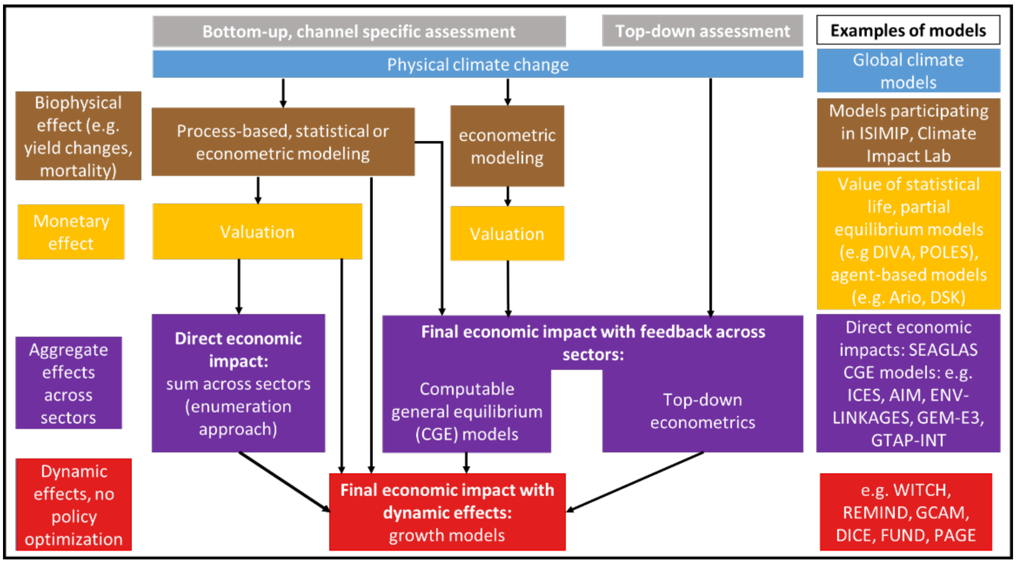

Figure 1: (taken from Piontek et al. 2021, Figure 1): Taxonomy of approaches to capture economic impacts of climate change. The different end points capture different levels of feedback effects.

Table 1 provides a summary of those approaches, while Figure 2 shows an overview of resulting damage estimates. The great uncertainty of damage estimates, ranging from global GDP losses between 3 and 65% for a 4° increase in global mean temperature above pre-industrial levels, shows the great gaps in this field. The paper discusses reasons for this, putting a focus on the open question whether damages affect the level of economic output or the growth rate, which is key in empirical estimates of damages. Another focus is on the limits surrounding bottom-up assessments using CGE modeling, including the incompleteness of types of impacts being included and the lack of uncertainty surrounding impact estimates. Other key gaps highlighted are the challenge of aggregating and that distributional effects or adaptation are not included in most economic models. The paper suggests multiple ways forward: (i) Given the difficulties in the economic valuation of impact channels and the great gaps in coverage (notably extreme events, health and human capital, biodiversity and ecosystem services, conflict and migration), priorities should be developed which impacts to focus on in a collaborative setting between impact modelers and economists. Combination of different methodologies (bottom-up and top-down) should be investigated while avoiding double counting. (ii) Economic and integrated assessment models should be advanced structurally, in particular with respect to resolution and adaptation. Alternative welfare measures are needed to avoid a focus on GDP loss. (iii) Structured model intercomparisons including different types of models with a focus on impacts are required to understand relevant dynamics and the reasons for the large differences.

Table 1 (taken from Piontek et al. 2021, Table 1): Comparative overview of aggregate global economic damage estimates following three main different approaches as shown in Figure 1.

	Direct economic impacts	**Final economic impacts with sectoral feedback effects**		**Aggregate damage functions**
	Bottom-up assessment	***Bottom-up assessment***	***Top-down assessment***	
Approach	Add up damages from individual sectors (either from	Overall economic effect of direct sectoral damages	Econometric study of aggregate climate	Apply aggregate damage functions in growth models

	biophysical models or from econometric studies)	including equilibrium effects, autonomous adaptation endogenous	effects as well as individual channels	to capture economic feedback, for example, from investment; often used for CBA to derive abatement decisions
Impact channels	Various, most prominently agriculture, labor productivity, tourism, health (infectious diseases, heat-related mortality), energy demand, limited sea-level rise		(Total) factor productivity or growth	Output loss
Examples	Roson & Satori (2016)	Kompas et al. (2018)	Burke et al. (2015)	Howard & Sterner (2017)
Global GDP loss for different warming levels (see also Figure 2)	1.5°C: 1%	1.8°C: 0.5%	1.5°C: < 10%	1.5°C: slight gains under the FUND damage function, up to 3% loss under … with productivity effects
	4.3°C: 6-8%	4°C: 3%	4.3°C: 5-65%	4°C: 1-18% loss
	(based on two studies)	(based on three studies)	(based on six studies)	(based on four studies)
Advantages	Transparency; high detail on impact side		Close derivation from observed data; full representation of (historical) uncertainty; simple representation for use in IAMs (with caveats)	Simple function for use in IAMs; high flexibility
	Includes non-market damages (for example, mortality impacts via the statistical value of life); direct consideration of explicit adaptation measures	Captures economic response dynamics for different impact channels; high sectoral detail; propagation of impacts across sectors		
Disadvantages	Little flexibility on impact side; rare uncertainty analysis (often a single biophysical impact model per channel)		Focus on output/productivity effects – rarely includes other channels such as extreme events; opacity about included channels	
	No feedback/interaction	No forward-looking	Out-of-sample projections;	Difficult to derive; high aggregation

	effects between sectors, from the general economy or to the climate system	investment processes; cannot capture economic transformations; spatial resolution limited by input/output data	unclear role of adaptation; assumes stationarity in slow-moving processes (for example, cannot capture sea-level rise); does not include non-market damages	masks spatial/social heterogeneity

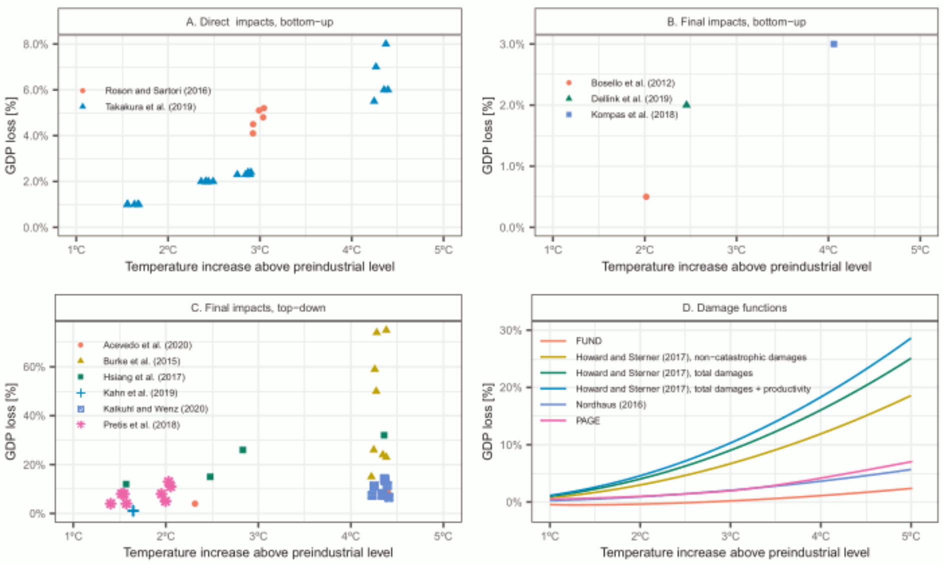

Figure 2 (taken from Piontek et al. 2021 Figure 2): Global GDP losses at increasing warming levels, estimated with different modeling approaches. (a) Direct economic impacts based on bottom-up assessment. (b) Final economic impacts with sectoral feedback effects based on bottom-up assessment. (c) Final economic impacts with sectoral feedback effects based on top-down econometric studies. (d) Aggregate damage functions from the prominent cost-benefit models DICE, FUND and PAGE, and from the meta-analysis by Howard & Sterner (2017) with different specifications.

Based on the work on this paper, several authors (F. Piontek, L. Drouet and A. Méjean) also contributed to the cross-working group box on economic damages in the 6th Assessment Report of the Intergovernmental Panel on Climate Change (Rose et al. 2022, Guivarch et al. 2022).

Complementary to this review of existing aggregate economic damage estimates Rising et al. (2022) provide a perspective focusing on the risks and uncertainties associated with climate change missing in those estimates. A first focus of this paper is on different types of uncertainty and the need to include many of these in economic assessments (Figure 3). A key argument is that decision-makers are more adept at dealing with uncertainty than typically assumed, as they also handle uncertainties in other areas like public health, and that such uncertainty has a large effect on economic estimates and decisions even without well-quantified probabilities.

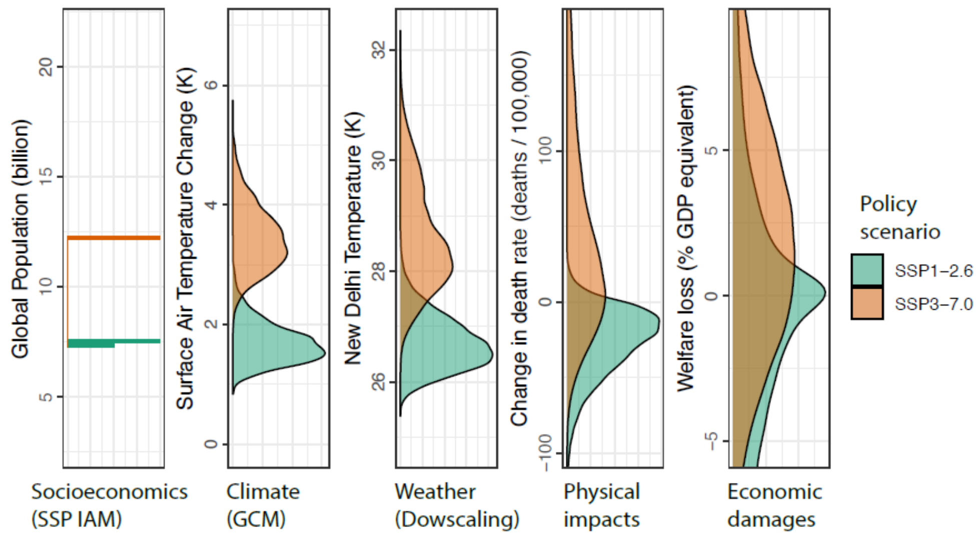

Figure 3 (taken from Rising et al. 2022, Figure 1): Compounding uncertainty in climate risks estimation across different stages of analysis. Distributions are shown for an illustrative projection of changes to death rates in New Delhi (using data from Carleton et al. 2022).

The paper proceeds to provide an ontology of missing risks, briefly summarized in the following:

- Missing biophysical impacts: This category corresponds to Piontek et al. (2021) as it focuses on the challenge of including state-of-the art biophysical impact knowledge into economic estimates. Interdisciplinary collaboration is a key to overcome this gap.
- Spatial and temporal extremes: Aggregate and optimization-focused economic approaches miss key dynamics from extremes. The paper discusses how to improve the treatment of heterogeneity, variability and uncertainty in the modeling chain from climate to biophysical to economic impacts as well as in communication with decision makers. Key components are to drive impact models by downscaled climate inputs at monthly or higher frequency over multi-decadal periods, capturing the interaction between the dynamic uncertainty from the natural variability of the climate system and of climate change. Probability distributions over parameter values, obtained from Monte Carlo simulations across multiple GCMs and impact models, capture parameter uncertainty in impact models. Finally, variability and uncertainty should be separated when communication with users, while stating clearly model inadequacy and unmodeled risks.
- Feedback risks and interactions: Feedbacks and compounding effects can trigger cascading effects, tipping points, lower thresholds for substantial impacts or lead to deeper impacts. As these are largely underrepresented due to their complexity, risks are severely underestimated. New approaches like agent-based modeling may be helpful, as well as more interaction between climate and social scientists.
- Deep uncertainty: This refers to processes for which no robust probability distributions are available. A particular example are black swan events – events of extreme nature and severe long-lasting consequences which are outcomes from the tails of heavy-tailed probability distributions. They can be positive (e.g. sudden technological breakthroughs) or negative (conflict, unforeseen ecosystem changes, disease outbreaks). One avenue of exploration is scenarios, which currently typically not capture disruptive deviations from the historical path. Storyline approaches exploring the vulnerability of policies to disruptions can be used.

- Unidentified risks: These include completely unexpected risks, like unpredictable responses of populations or yet unknown natural mechanisms sensitive to climate. The precautionary principle is one way of addressing these, lessons can be learned also from complexity science.

The paper discusses ways forward to include some of these risks. A broader research agenda includes three overlapping stages: (i) assessing and incorporating the existing knowledge of risks more comprehensively in total risk assessments; (ii) map out gaps in current models and how to fill them by improving the models or develop non-model based approaches; (iii) long-term research with targeted funding for interdisciplinary engagement and the development of new model and non-model based approaches to robustly test the sensitivity of policy-relevant conclusions to the non-linear consequences of risks and uncertainty. In addition, the paper presents an approach to quantify missing risks by combining existing, uncertain and qualitative information on a growing collection of risks. It is built on a copula approach and requires a consistent metric across different risks. An example is provided using people at risk (Figure 4).

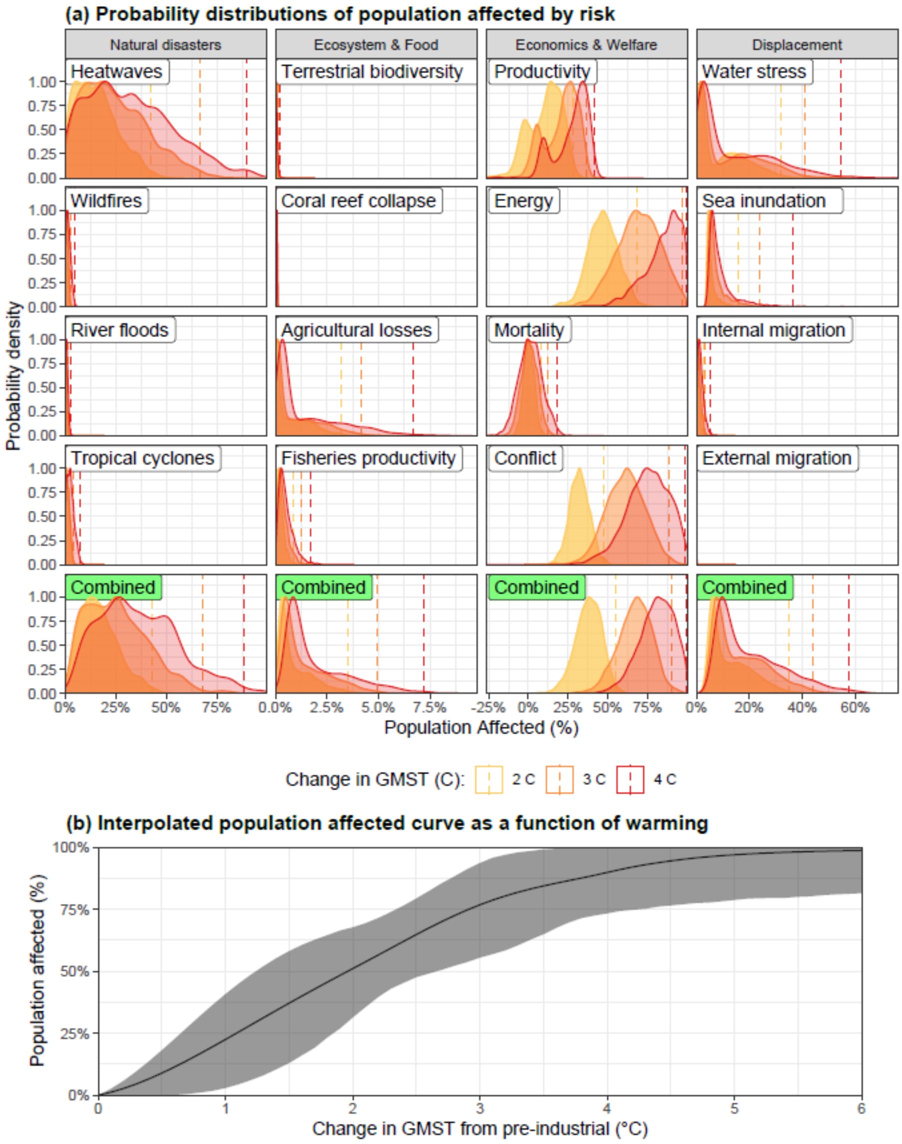

Figure 4 (taken from Rising et al. 2022, Figure 4): Distributions of projected population at risk. (a) Each panel shows the distribution of the portion of the global population that could be impacted by a risk or a combination of risks. Each distribution is based on a single study, the collection of risks is not comprehensive. The dashed lines represent the 99th percentile of the distributions. See Rising et al. 2022 for more details. (b) Smooth spline representation of the combined population affected across all risks shown in panel (a). Spline is fit to each Monte Carlo drawn value at 2, 3 and 4°C. Shaded region shows the 1-99th percentile.

2.2. Economic impact quantifications

2.2.1. Labor productivity and supply (Dasgupta et al. 2021)

The impacts of climate change on labor are one of the key channels for aggregate productivity losses and therefore, economic effects of climate change. They are also crucial for distributional effects due to the differences in exposure and adaptive capacity of different income groups due to their predominant type of labor. Despite this crucial importance, no robust, global estimate for labor impacts has been available. Instead, quantifications used in IAMs relied on few studies using very different metrics based either on purely physiological arguments or on very small data samples. Dasgupta et al. (2021) provide a systematic and comprehensive assessment of labor impacts. First, the paper clearly defines labor productivity (work performance during working hours, physiological) and labor supply (working hours, relevant for economic quantification, affected by climate change through reduction of hours), as well as combines both dimensions into a metric called effective labor, calculated as

*Change in effective labor = (100% + change in labor supply) * change in labor productivity*.

For labor productivity, different exposure response functions from the literature are intercompared for the first time. Differences among them are large (Figure 5, Panel 1), for the quantitative estimates in the paper an augmented mean is used. Note that they are driven by changes in wet-bulb globe temperature (WBGT), a measure including the effects of humidity, but difficult to calculate realistically from modelled rather than observed data. Details on the calculation method can be found in the paper. Exposure response functions for labor supply are estimated through an empirical approach, using micro survey data on hours worked per week from the IPUMS-International (Integrated Public Use Microdata Series) archive, covering multiple countries and a period of 30 years. The estimation uses the following panel regression, depending on type of labor (low or high exposure, where low exposure refers to indoor or outdoor in the shade) s, region i and survey year t: $\ln(LS_{ist}) = f_s(temp_{ist}) + \alpha_{is} + \gamma_{ts} + \varepsilon_{it}$. Here the dependent variable is the total number of hours worked, *temp* is either regional annual mean temperature or WBGT and both linear and quadratic temperature dependencies are included, α and γ are the time-invariant subnational and survey-year fixed effects. Estimates were done globally, as well as for selected regions (Africa, Asia, the Americas and Europe). Climate input data were taken from ERA 5[1]. Results are shown in Figure 5 (Panel 2), featuring a non-linear, concave relationship between mean temperature and labor supply, with region- and sector-dependent optimal temperatures ranging between 14-25°C for low and 11-21°C for high exposure, meaning higher heat stress for workers.

[1] **https://cds.climate.copernicus.eu/cdsapp#!/home**

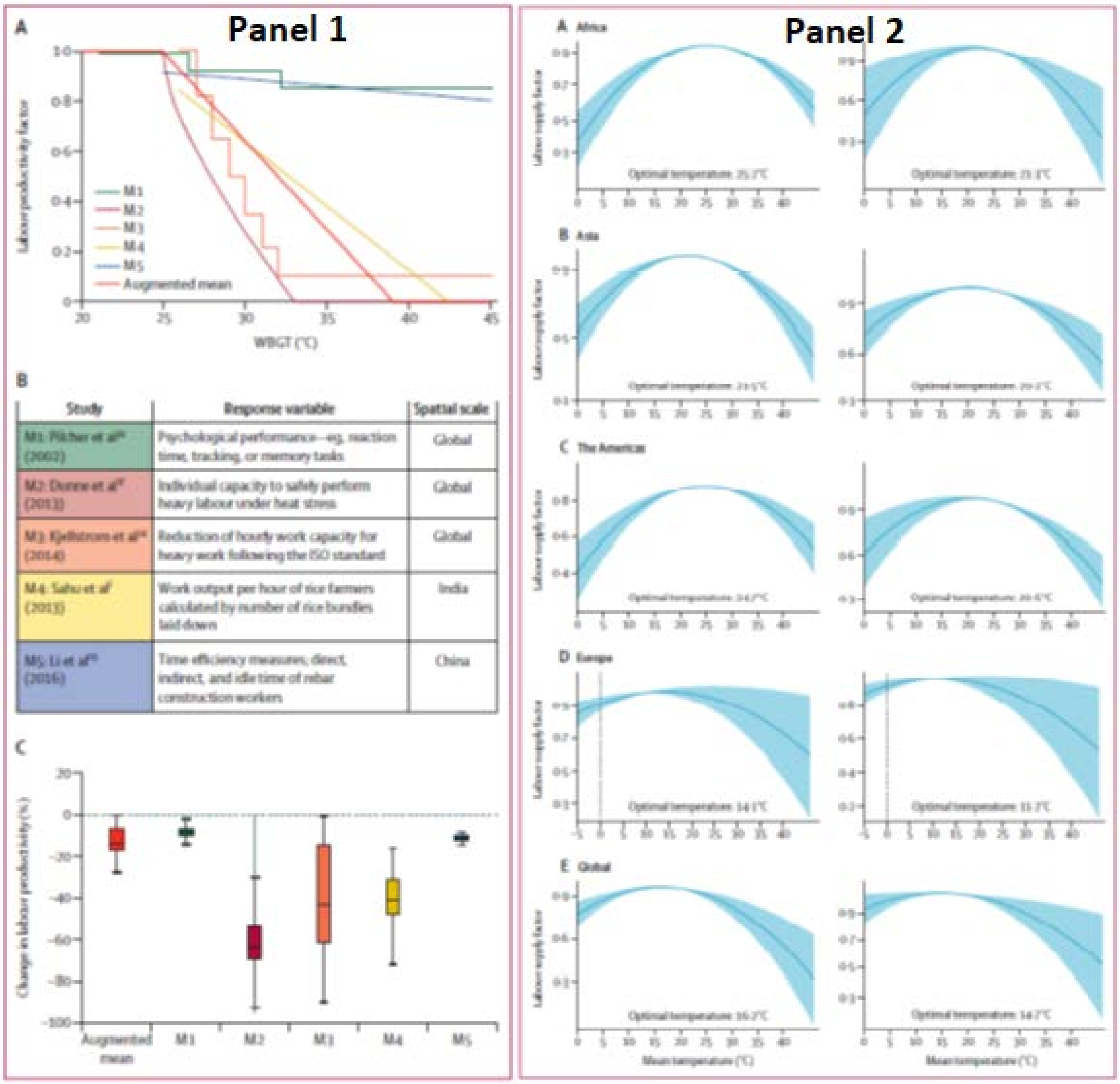

Figure 5 (taken from Dasgupta et al. 2021, Figures 1 and 2): Panel 1: Exposure response functions for labor productivity. (a) The 5 individual response functions from selected impact models used to calculate the augmented mean response function (red line) which is applied in this study for labor productivity effects of WBGT. (b) Overview of the labor productivity impact models with their response variable and spatial scale. (c) Global effects of climate change on labor productivity for the augmented mean response function and individual labor productivity impact models at 3°C compared with the historical baseline period (1986-2005). Boxes show the quartiles and the horizontal line in the box shows the median, whiskers denote the most extreme non-outlier data that extend beyond the whiskers. Panel 2: Relationship between temperature and labor supply from empirical estimate. Shading shows 95% confidence interval. The left column shows results for low exposure (indoor or outside in the shade), the right column results for high exposure (outside in the sun).

The paper uses the ERFs for labor productivity and supply to study present day limits to labor output, caused by temperatures deviating from the optimal temperatures. Note that for labor productivity and effective labor, WBGT is used instead, and for labor productivity only effects from higher than optimal temperatures are included due to the nature of the ERFs. Already today, labor is impeded by climate, most importantly in the tropics, but also in higher latitude regions (Figure 6 A). Global mean annual effective labor is a factor of 0.23 below the theoretical optimum. This is exacerbated by future climate change, examined at increases of global mean temperature of 1.5, 2 and 3°C. Note that these projections, based on climate projections from the ISIMIP project (Frieler et al. 2017), do not account for adaptation. Global effective labor at low exposure conditions will decrease by 6.7 percentage points under 1.5°C warming and by 18.3 percentage points under 3°, with large differences between regions. (Figure 6 B). For high exposure conditions the effects are significantly higher. As a multitude of adaptation options are possible in the labor sector (e.g. air condition, shifts in working hours, change of sector) these estimates therefore represent a worst case.

This study provides a crucial contribution to impacts estimates, for the first time providing a global, regionally differentiated, empirically based estimate for labor supply effects in a way which can be used by IAMs and CGE models, as well as transparently comparing multiple available ERFs for labor productivity. Key results include the need for regional differentiation when calculating the effects and the need to include multiple ERFs for productivity effects due to their large differences. Future planned research includes estimating the effects of adaptation, studying the persistence of the effects and providing a complementary, empirically based study of labor productivity effects. The use of WBGT also warrants further investigation.

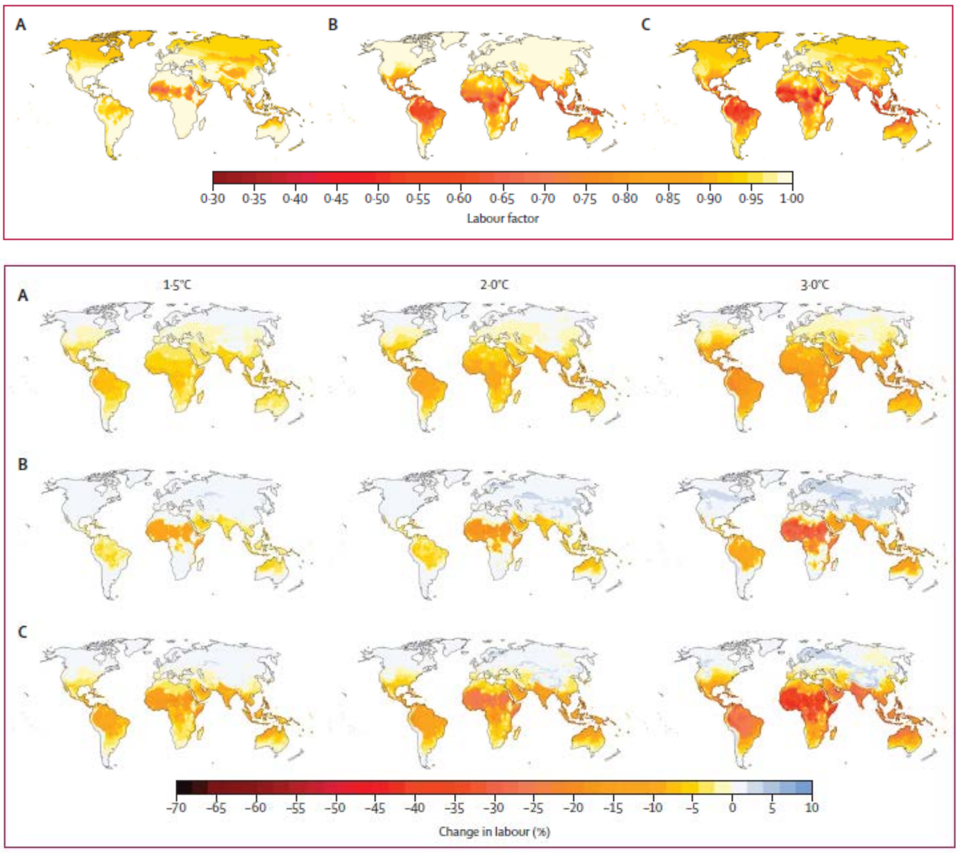

Figure 6 (taken from Dasgupta et al. 2021, Figures 3 and 4): (A) – labor supply factor, (B) – labor productivity factor, (C) – effective labor factor = combination of A and B. Top: Effects of climate on labor, 1986-2005. Bottom: Effects of future climate change relative to the period 1986-2005 on labor, for 1.5, 2 and 3°C warming. All are for low exposure conditions, i.e. indoors or outdoors in the shade.

2.2.2. Tropical cyclones (Krichene et al. 2022)

Extreme events are one of the key missing factors in most economic damage estimates, due to the lack of robust, global quantifications of these damages under future climate change. Tropical cyclones (TCs) are among the most harmful extreme events, affecting millions of people and causing an average of 52 billion US$ annually over the last decade (CRED EM-DAT). In addition to the direct losses, there is increasing evidence that TCs affect economic growth, i.e. causing effects which persist for years after the event (Krichene et al. 2021). This can even hamper development perspectives, especially when the economic effects of multiple events overlap. As future climate change is expected to intensify TCs in the future, they are critical to include in integrated assessment. By focusing on the question of long-term persistence and country level heterogeneity as well as deriving a damage function which can be readily applied in IAMs Krichene et al. address three important research gaps. Building on the metric of people affected the results of this study can also be linked to future studies of other types of extreme events (see e.g. Lange et al. 2020). The paper builds a multi-step analysis framework, starting from an empirical estimation of the relation between economic growth and tropical cyclones in the historic period 1971-2015, analyzed for 41 cyclone-prone countries (Figure 7a). They use a three-way fixed effect panel regression with annual national shares of people exposed to cyclones as predictor (thereby avoiding endogeneity issues), covering different lag years: $g_{i,t} = \gamma_i + \delta_t + \theta_i t + \sum_{l=0}^{L} \beta_l P_{i,t-l} + \epsilon_{i,t}$. Here, g is the growth rate of country i at year t, γ, δ and θ are country and time fixed effects and country-specific time trends, while ϵ is the error term. The sum describes the cumulative response of a country i to the national shares of people exposed to TCs (P) in year t-l, with l lag years. β describes the average growth response across all countries. The optimal number of lag years is estimated as 9 (see paper for details on this). Uncertainty is captured through a maximum entropy bootstrapping method. Results show heterogeneous historic responses for different countries with effects leveling out after 6-8 lag years (Figure 7b).

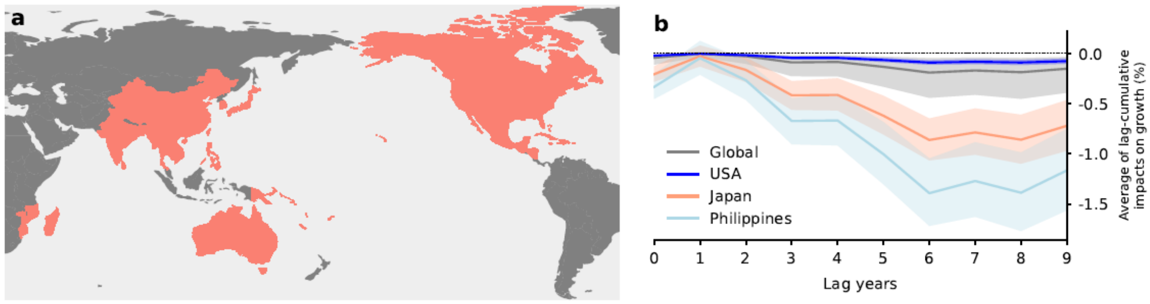

Figure 7 (taken from Krichene et al. 2022 Figure 1): Long-term economic growth response to tropical cyclones. (a) Map of the set of 41 countries exposed to tropical cyclones and considered in the analysis. (b) Average historical response of per-capita GDP growth to tropical cyclone exposure as a function of lag years for selected countries (colors) and on global average (gray). Shaded areas indicate the 66% confidence intervals.

The second analysis step is the derivation of projections of TC damages under future climate change. The study takes into account five dimensions of uncertainties and dependencies, mapped out through a combination of bootstrapping and scenario analysis. This includes

- the uncertainty of the historical growth response as shown in Figure 7b, covered through 1200 bootstraps per country
- the uncertainty of future TC occurrence, captured through the use of a TC impact emulator generating 100 probabilistic time series of TCs for 9 ocean basins, 4 global climate models and 3 RCP scenarios (see below)
- the uncertainty of future greenhouse gas emissions and socioeconomic conditions, captured through the use of different Representative Concentration Pathways (RCPs, including RCP2.6, 6.0 and 8.5) and two socioeconomic scenarios (Shared Socioeconomic Scenarios SSPs 2 and 5)
- the normative uncertainty around discounting, covered by four different assumptions for the discount rate (Stern: 3 different values from the Stern review (Stern 2008); Nordhaus: standard calibration of the DICE model (Nordhaus 2012); Ricke: Ricke et al. 2018).

Covering all of these dimensions the study derives projections for the discounted annual damages by future cyclones over the period 2021-2100, comparing national GDP trajectories with and without the

effects of global warming. Importantly, a “no climate change” baseline calculates the effects of tropical cyclones based on present day climate, assuming these damages are not included in the baseline SSP GDP projections. Future GDP trajectories with TC effects are calculated as $y_{i,t+1}^{e\ or\ bl,\ s,m,r,b,l} = y_{i,t}^{e\ or\ bl,\ s,m,r,b,l} e^{g_{i,t}^{s}+\Phi_{i,t}^{e\ or\ bl,s,m,r,b,l}}$ where g is the country-specific GDP growth rate from the SSP GDP projections and Φ is the empirically estimated TC damage given by $\Phi_{i,t}^{e\ or\ bl,s,m,r,b,l} = \sum_{l'=0}^{l} \beta_{l'}^{b,l} P_{i,t-l'}^{e\ or\ bl,s,m,r,b}$. “e or bl” indicates RCP projection or no climate change baseline, s, the SSP scenario, m the global climate model, r the TC realization and l the number of lag years. The discounted annual damage is finally defined as the discounted difference between the GDP of the “no further climate change” (bl) scenario and the corresponding scenarios for the different RCPs: $DAD_{i,t}^{e,s,m,r,b,l} = y_{i,t}^{bl,s,m,r,b,l} - y_{i,t}^{e,s,m,r,b,l} \prod_{\tau=2021}^{t} e^{-r_{i,\tau}^{bl}}$ where $r_{i,\tau}^{bl} = \rho + \eta g_{i,t}^{bl}$ is the growth-adjusted discount rate with pure rate of time preference ρ, consumption elasticity of marginal utility η and baseline GDP per capita growth rate at year t g.
Again, it is assumed that the economic vulnerability of countries does not change in the future, i.e. no adaptation will take place, leading to a likely overestimation of effects. Results are shown in Figure 8. In terms of absolute losses, strongly exposed high income countries like Taiwan, Hong Kong or Japan are highly affected, though when expressed in percent of 2019 average household income, small island developing states like the Bahamas or Mauritius, but also Vietnam or the Philippines see strong effects.

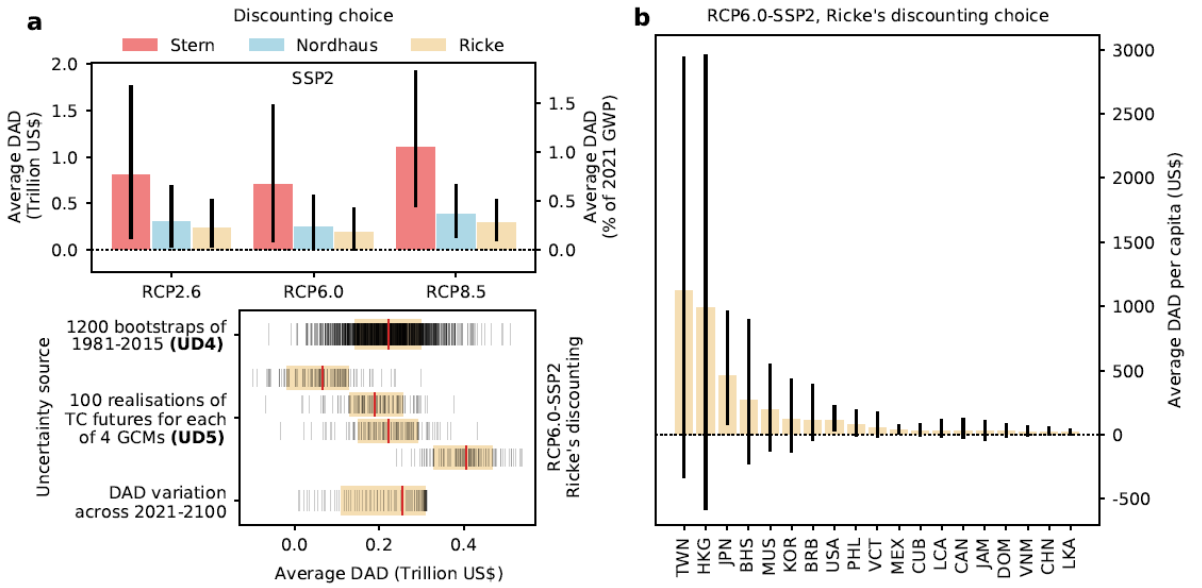

Figure 8 (taken from Krichene et al. 2022 Figure 2): Discounted annual damage of tropical cyclones. (a) upper panel: Median global discounted annual damage (DAD) from tropical cyclone impacts averaged over the period 2021-2100 for three RCPs (2.6, 6.0, 8.5), two SSPs (SSP2 and SSP5) and three different values of the growth adjusted discount rates used in the Stern review, for the standard calibration of the DICE model and by Ricke et al. Black whiskers indicate the 66% confidence interval accounting for uncertainty from the historical growth response of countries to tropical cyclones and from the response of tropical cyclone impacts to future greenhouse gas emissions. (a) lower panel: Quantification of uncertainties for the main specification (RCP6.0-SSP and Ricke’s discounting choice). The uncertainty drivers listed on the y-axis are allowed to vary, all other dimensions of uncertainty are averaged out. Each vertical line is a point estimate. Red lines and shaded boxes denote the median and 66% confidence interval across each of the listed sources of uncertainty, respectively. (b) Median country-level per capita DAD averaged over the period 2021-2100 for the 20 most impacted countries and the main specification. Black whiskers are as in (a) upper panel.

The next step in the analysis is the derivation of a country-level TC damage function through a linear regression growth rate changes with global mean temperature change $\Delta T^{e,m}$: $\Phi_{i}^{s,e,m,r,j,l} = \gamma_{i}^{r,b,l} +$

$\omega_i^{r,b,l}\Delta T^{e,m} + \epsilon_i^{r,b,l}$. The coefficients are independent of emission and socioeconomic pathways as the fit is performed across the combination of all RCP-SSP scenarios.

When dividing countries into four groups depending on their level of development, the study finds similar shares of significantly negatively affected countries across all groups, illustrating that the growth losses are not driven by development but rather by country-specific characteristics. Importantly, also highly developed countries can expect to see significant damages from TCs under future climate change without additional adaptation measures. Figure 9 shows the country-specific effects of a 1°C change in GMT.

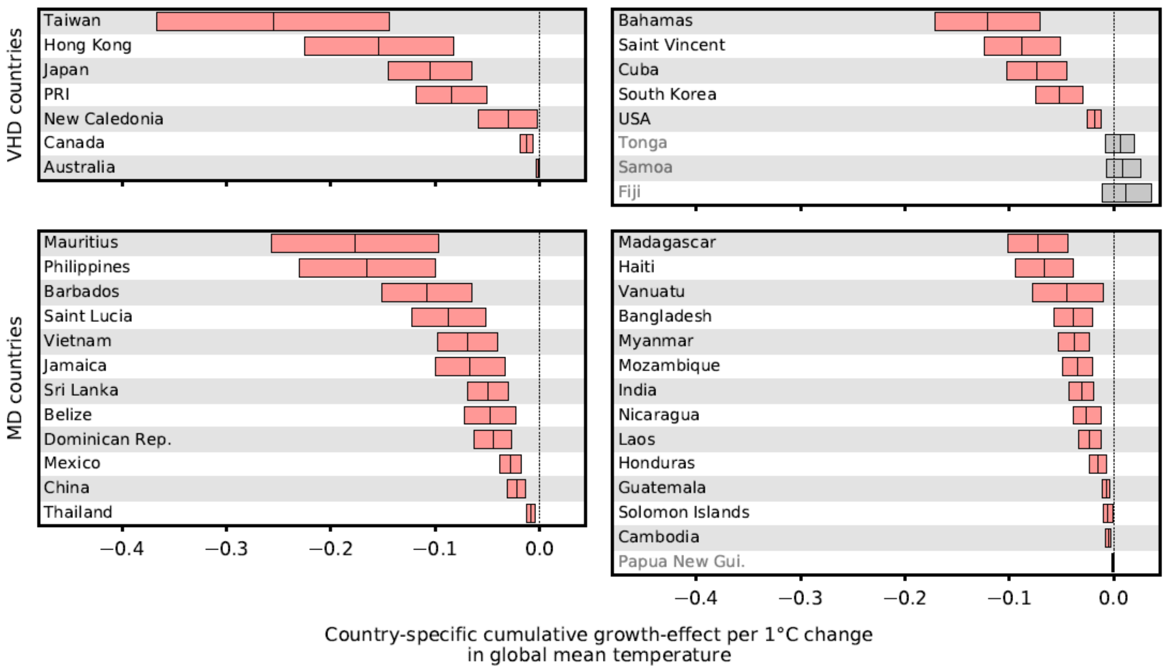

Figure 9 (taken from Krichene et al. 2022 Figure 3 panel b): Temperature-dependent damage functions for tropical cyclone induced growth losses. Country-level growth rate changes per degree of global mean temperature change for very highly developed (VHD), highly developed (HD), medium developed (MD) and least developed (LD) countries (classification according to the inequality-adjusted human development index). Black vertical lines and boxes indicate median losses and 66% confidence intervals, respectively, and red and gray colors denote statistically significant and non-significant results, respectively. These results are for 9 lag years and Ricke's discounting choice.

The final step in the analysis is a calculation of the social cost of carbon of tropical cyclones. The social cost of carbon is a crucial measure for policy makers and, as it relies on available damage functions, typically does not include the effects of extreme events. It denotes the marginal response to an emission pulse of an additional 1 GtC in the year 2021. Figure 10 shows country-level contributions to total SCC for selected countries and different discount rates, where the non-TC SCC is calculated based on the Burke et al. damage function (Burke et al. 2015). Globally, TCs increase the SCC by 2.1% from 406 US$/tCO2 to 415 US$/tCO2. The contribution from TC-affected countries to the global SCC increases by 3%. Figure 10 (right side) shows that in particular for TC-prone high-emitting countries like the US, China and Japan have high increases in SCC from TC effects.

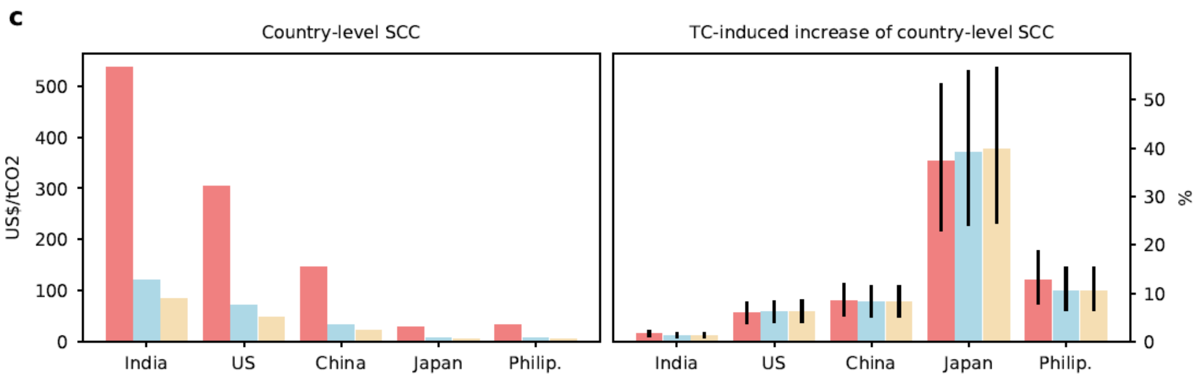

Figure 10 (taken from Krichene et al. 2022 Figure 4, panel c): Social cost of carbon from tropical cyclones (results for 9 lag years, RCP6.0-SSP2). Left: median country-level SCC from Ricke et al. for aggregate damages. Right: their increases from tropical cyclone effects. Colors: discount rates as in Figure 8 panel a top.

2.2.3. Other types of extreme events

Floods

Fluvial floods are another main category of extreme weather events causing substantial economic losses around the globe. For instance, since 1980, fluvial floods have caused more than 200,000 fatalities and more than $790 bn in direct economic damages globally (Emrich 2013), placing them among the most socially and economically devastating natural disasters. Theoretical considerations on the global surface energy budget suggest that global mean precipitation increases with global mean temperature (GMT) at a rate of 1-2% per K of global mean warming (Trenberth 1999). However, the intensity of extreme precipitation events is most relevant for fluvial flooding (Ivancic & Shaw 2015) and increases with the moisture of air that can be precipitated out according to the Clausius-Clapeyron relationship (Boer 1993). Therefore, extreme daily precipitation is expected to increase at a substantially higher rate of ~6-7% per K of global mean warming (Allen & Ingram 2002). These theoretical considerations were recently confirmed by observations showing a global median increase in annual maximum daily precipitation of 5.9% to 7.7% per degree of global warming (Westra et al. 2013). In addition, there are more record-breaking rainfall events observed than would be expected in a stationary climate (12% increase in 1981–2010, Lehman et al. 2015) and the observed intensification of extreme daily precipitation events since the 1980s has been attributed to anthropogenic global warming (Fischer & Knutti 2016). Observed annual discharge maxima show regionally varying trends with significant increases in most stations of Asia, Europe and Latin America and with mostly decreasing trends in Africa, Australia and North America (Do et al. 2017). Globally, 1985-2009 flood frequency has first increased, peaked around 2003, and decreased afterwards (Najibi & Devineni 2018). Extreme flood events show a similar non-monotonous temporal evolution with strongest long-term trends in Europe and the United States of America (Berghuijs et al. 2017). On global and latitudinal scales the observed variation in flood frequencies can be statistically explained by variations of four decadal and multi-decadal climate oscillations: the El Niño–Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO), and the Atlantic Multidecadal Oscillation (AMO) (Najibi & Devineni 2018).

A paper by Sauer et al. (2021) studied to what extent the observed changes in climate have already induced long-term trends in economic damages caused by fluvial flooding. To disentangle the impact of climate induced changes in weather-related hazards (flood extent and depth) from changes in exposure of assets, and their vulnerability, we develop a hybrid process-based and empirical model.

First, it overlays annual flooded areas derived from hydrological simulations forced by observational weather data (Jongman et al. 2015, Tanoue et al. 2016) with spatially and temporally explicit asset distributions. The exposed assets are then translated into direct economic damages by combining continental depth-damage functions with time dependent vulnerability factors (Jongman et al. 2015, Tanoue et al. 2016, Formetta & Feyen 2019).

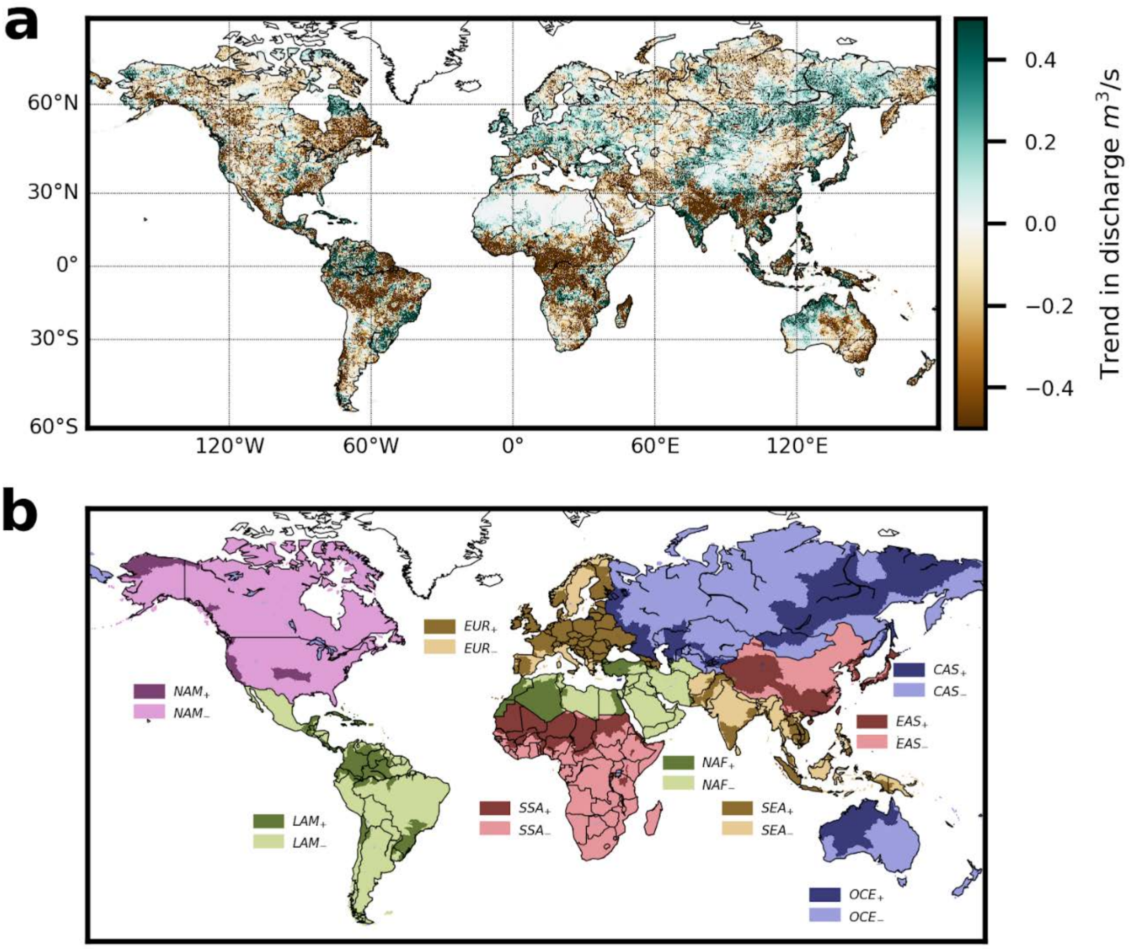

Figure 11 (taken from Sauer et al. 2021 Figure 1): Discharge trends and definition of regions. (a) Absolute trends in annual maximum daily discharge in the time period 1971-2010 (b) Map of the nine geographical world regions: North America (NAM), Eastern Asia (EAS), Europe (EUR), Latin America (LAM), Central Asia & Russia (CAS), South & Sub-Saharan Africa (SSA), South & South-East Asia (SEA), North Africa & Middle East (NAF), Oceania (OCE) chosen according to geographical proximity and similarity of socio-economic structure. These regions are then further divided into subregions assembled of river basins with positive (R+, dark colors) and negative discharge trends (R-, light colors).

When analyzing the contributions of the individual drivers (climate induced changes in weather-related hazards, changes in exposure and changes in the vulnerability of assets) to damage trends, we focus on regions where the full model accounting for all three drivers explains at least 20% of the variance in reported damages (in units of inflation adjusted 2005 purchasing power parities (PPP) USD) indicating that at least part of the critical processes determining the variability in damages are captured. In North America (NAM) (see Fig. 11a for a definition of the regions), the explanatory power is exceptionally high in the entire region and in the subregion with negative discharge trend (RNAM2> 80%, RNAM-2 > 90%) (Fig. 12). Further, high explanatory powers of more than 50% are reached in Eastern Asia (EAS) and its subregion with positive discharge trend (EAS+), in Oceania (OCE) and its subregion (OCE-) with negative discharge trend, as well as in the subregion of South & South Eastern Asia with positive discharge trend (SEA+). Further, acceptable explanatory power (R2> 20%) is reached in Western Europe (WEU), Latin America (LAM) and its subregion with positive discharge trend (LAM+), as well as in the positive (negative) discharge subregions of Central Asia (CAS+), (Eastern Asia EAS-)). Globally, the explanatory power of the model exceeds 30% and is slightly higher across basins with positive discharge trends (RGLB+2= 45.5%).

To analyze how much of the variability can be explained by what driver, we additionally provide the explained variances of modeled time series accounting for i) changes in flood hazards only and for ii) changes in hazard and exposure. In most regions and subregions accounting for climate-induced variability and trends is key for reproducing observed damages. In most cases, the explained variance only gets slightly improved by additionally considering changes in either only exposure or both exposure and vulnerability with the exception of SEA+, OCE and OCE- where explained variance increases strongly, and EAS- and LAM- where it decreases.

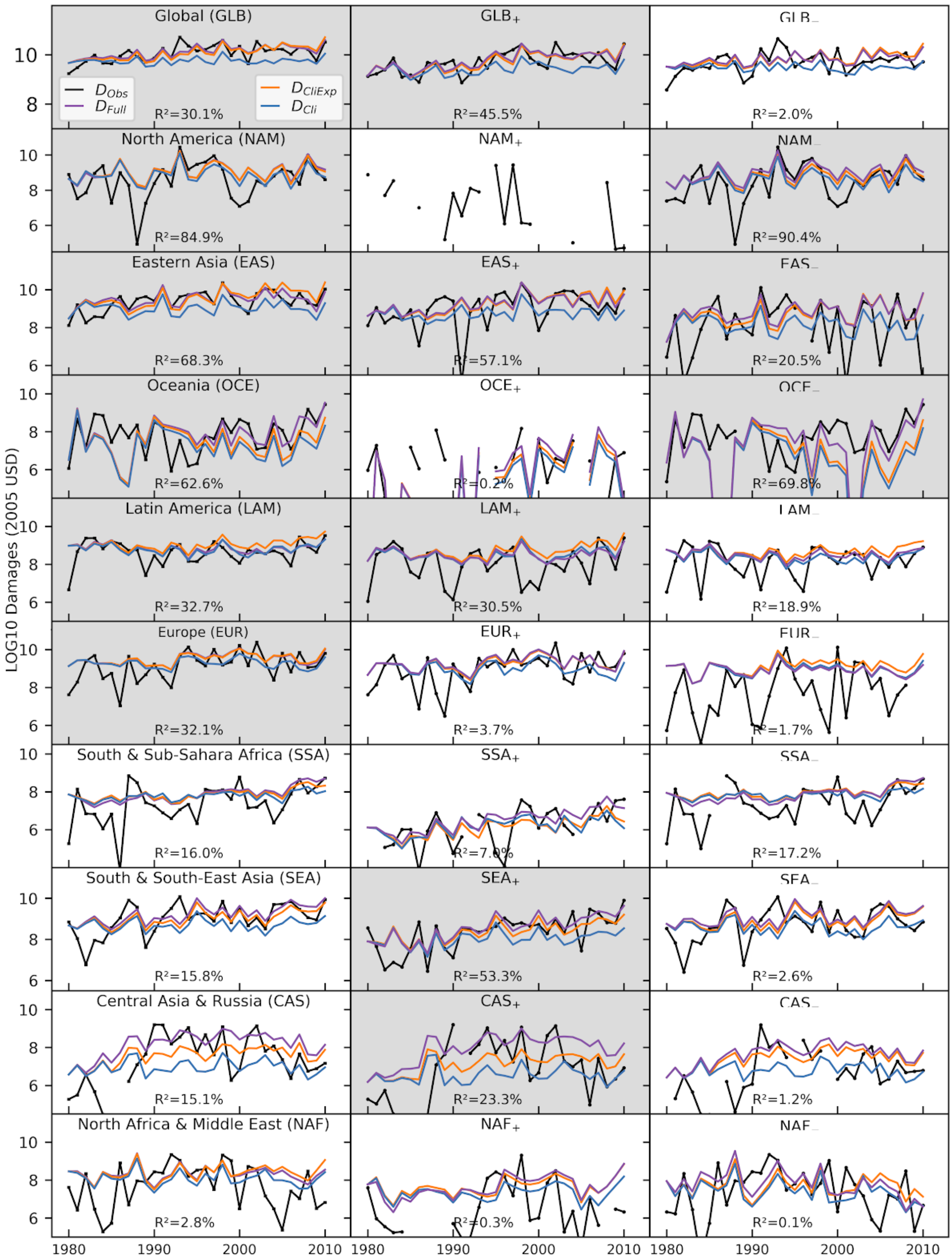

Figure 12 (taken from Sauer et al. 2021 Figure 2): Observed and modeled time series of river flood damages (1980-2010). ime series of observed damages DObs (NatCatService database1 (black) as well as modeled damages (multi-model median) when accounting for changes in i) climate only (constant 1980 socio-economic conditions, D1980, blue), ii) climate and exposure (DCliExp, orange) keeping vulnerability at 1980 conditions, and iii) in climate, exposure, and vulnerability (DFull, purple) over time for the nine world regions (left panel), as well as their subregions with homogeneous positive and negative trends in river discharge (middle and right panels). Explained variances R2 are derived from the correlation coefficients between damages of the full model with observed damages.

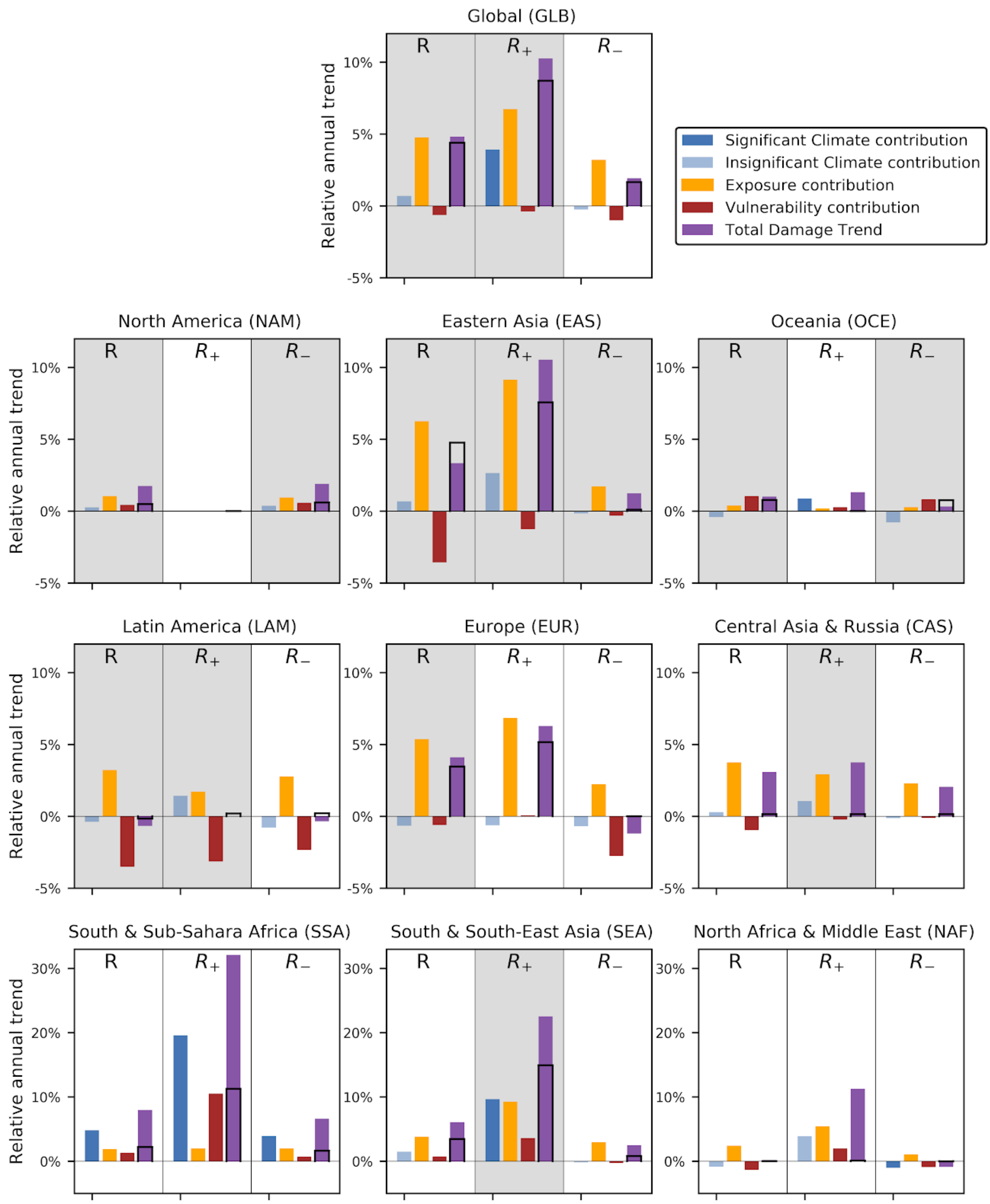

Figure 13 (taken from Sauer et al. 2021 Figure 3): Contributions of changes in climate, exposure, and vulnerability to damages induced by river floods (1980-2010): Bars indicate the relative trend in annual modeled (purple) and observed damages (black frames) and the individual contributions of each driver: climate variability (blue), exposure (orange), vulnerability (red) relative to the recorded annual mean damage of the baseline period 1980-1995. From left to right, we present the trends in the entire world regions (R), and the subregions with positive (R+) and (negative, R-) discharge trends. Grey background colors highlight the regions where the explained variance of the full model is higher than 20%.

Climate-induced trends in damages are estimated from a restricted model accounting only for observed changes in climate while keeping exposure (in units of inflation adjusted 2005 purchasing power parities (PPP) USD) and vulnerability at 1980 levels (D1980). Damage trends induced by changes in exposure are then estimated from the difference between the trend in D1980 and the trend derived from an extended model additionally accounting for changes in exposure (DCliExp). Finally, damage trends induced by changes in vulnerability are estimated from the difference in trends between DCliExp and the full model (DFull).

In the full regions, comprising divergent trends in discharge, climate-induced trends in damages are small compared to exposure and vulnerability-induced trends and mostly insignificant except for SSA. However, when dividing the world regions into subregions with homogeneous discharge trends, climate-induced trends in damages become clearly detectable (Figs. 13) suggesting that in most regions trends in annual maximum discharge are a good proxy for climate induced loss trends. On global level a significant positive climate-induced trend emerges in GLB+ compared to the small and insignificant climate-induced global trend. In GLB+, as well as in SEA+, CAS+, and EAS+ the climate-induced trends are comparable or even larger than the trends induced by the socio-economic drivers. The same holds true for the climate induced trends in SSA+, OCE+, and NAF+ where however the explanatory power of the full model is considered too low (<20%) to allow for an attribution of observed damages. In most R+ regions, climate induced trends are positive and often significant, but relatively smaller and often insignificant in the corresponding R- region.

Future projections

We then used the developed modeling chain to project damages for different climatic futures until 2100. For that we used output of the global hydrological models participating in the second modeling round of the ISIMIP project (Frieler et al. 2017) for different future emission pathways and applied the same modeling steps as for the historical period keeping the empirically determined vulnerabilities at their historical levels. These damage projections will feed into the climate stress tests for the European banking sector developed by the Network for Greening the Financial System (NGFS) (Bertram et al. 2021) and have been made openly accessible via the open-access platform Climate Impact Explorer.

Outlook

Recently a new global satellite-based dataset for areas and people affected by fluvial and coastal floods became available (Global Flood Database). This dataset allows to improve the historical vulnerability analysis of (Sauer et al. 2021) with regard to a better understanding of the underlying drivers of vulnerability changes. By comparing vulnerabilities between regions we could show that frequently affected regions are less vulnerable suggesting adaptation efforts in the past period. We currently employ this result to generate a new set of future damage projections where we model future adaptation efforts on a regional level by allowing vulnerabilities in the future period to change according to past exposure.

Droughts

Beneath tropical cyclones and fluvial floods, droughts are one of the most damaging categories of extreme weather events. We are currently developing continental drought damage functions based on damages reported in the NatCatService database (NatCatSERVICE, 2014). We thereby use soil moisture anomalies and crop yield failures as predictors. Compared to often used meteorological indicators such as precipitation-evapotranspiration indices these impact indicators have the advantage to account for the exposure of vulnerable values and changes of exposure due to socioeconomic development (e.g., land-use changes) instead of merely describing unfavorable weather conditions. The impact indicators are either derived from ISIMIP simulations (historical period and different climate and socioeconomic futures) or from observational data sets (only historical period, e.g., Vegetation Health Index provided by the Center of Satellite Applications and Research of the NOAA). This approach will allow us to project damages for different future emission and socioeconomic development scenarios.

3. Application in integrated assessment modeling

3.1. The REMIND model

REMIND is an integrated assessment model providing an integrated view of transformations in the global energy-economy-climate-land system under scenarios for the future. It is typically used to answer questions like “Is it still feasible to reach certain climate targets?”, “How will the energy system have to transform to reach them?”, “What changes if we impose constraints like limits to bioenergy or nuclear energy?”. It represents 12 world regions and has a modular structure (Figure 14), consisting of a macro-economic core with a Ramsey-type growth model, a hard-coupled, detailed energy system and options to soft-couple to the reduced form climate model MAGICC and the land-use model MAgPIE. It calculates aggregate macroeconomic and energy-related investments for an inter-temporal Pareto optimum in the regions for the time frame 2005-2100, accounting for trade in goods, energy carriers and emission allowances between regions. Further details on the model can be found in Baumstark et al. (2021).

In the following sections we describe extensions to the REMIND model allowing to assess the effects of climate change damages. This is an important step towards truly integrated future scenarios assessing the interactions of damages and mitigation pathways, as well as the effects of both on inequality.

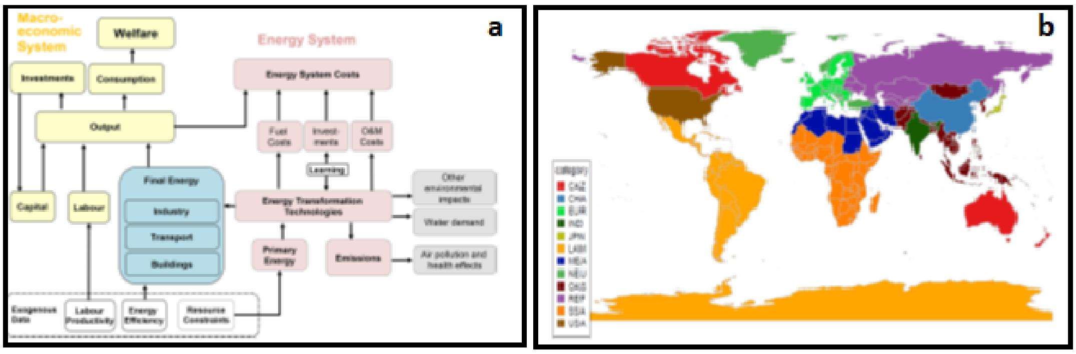

Figure 14: (a) Structure of the REMIND model. (b) Regions of the REMIND model.

3.2. Economic damages from on-going climate change imply deeper near-term emission cuts (Schultes et al. 2021)

Integrated assessment models are typically applied in two ways. The first is the cost-effectiveness mode, studying the optimal, most cost-efficient way to achieve a certain climate policy target, e.g. limiting gobal warming to well below 2°C as set out in the Paris Agreement, under various technological or political constraints. This approach ignores the reason why mitigation is done, which is to limit the damages of climate change, thereby missing to quantify the benefits of mitigation alongside its costs. In addition, it also misses the interaction effects of the damages occurring below the climate target, which might affect the transformation pathway and strategy as well as require adaptation. The second is the cost-benefit approach, weighting costs of mitigation and benefits from avoided climate change directly against each other to arrive at the cost-optimal outcome. However, this approach builds its optimal climate policy pathway on the damages entering the calculation, typically using aggregate, reduced-form damage functions. As currently available macro-economic damage functions are clearly under-representing the actual expected damages from climate change (see Chapter 1), this leads to higher emission scenarios then would actually be optimal.

Schultes et al. put forward a study integrating a long-term mitigation target of well below 2° with damages occurring at temperatures below that target and until it is reached. This safe-guards against catastrophic, unknown or unexpected climate outcomes above the target while acknowledging the existence of climate damages. It is still subject to uncertainty in the damage function but avoids the largest risks. It is dubbed "least total cost approach" (Figure 15).

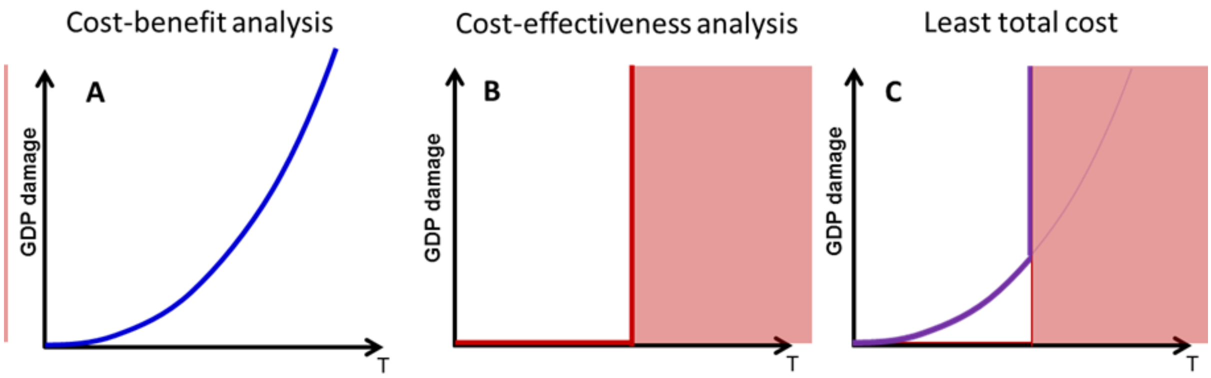

Figure 15 (taken from Schultes et al. Figure 1): Explicit or implicit economic damage functions in climate policy analysis (x-axis: global mean temperature). (a) Gradual economic damages accounted for in cost-benefit analysis. (b) CEA seeks to minimize mitigation costs for limiting warming below a given threshold, implicitly assuming zero damages below and infinite damages above the threshold. (c) LTC analysis combines both.

For this, Schultes et al. extend the REMIND model to allow the integration of damages. This is done via a flexible, soft-coupled approach, aiming to not increase the complexity of the optimization model too much and to allow for transparency and easy expansion of the damage module. Damages are endogenized in the model through the social cost of carbon, which enters as a carbon tax. Through an iterative approach until convergence, the effect of that damage-related tax on the mitigation strategy as well as the effect of the damages on the economic system are both accounted for. The social cost of carbon is calculated through an analytic approach detailed in Schultes et al. (2021).

The study uses the damage estimates by Burke et al. (2015), addressing the open question of persistence of damages by varying the persistence between 0 (pure level effect) and infinite (Burke result). This strongly affects the resulting social cost of carbon, making it the key uncertainty dimension in the final results. Other sources of uncertainty included are socioeconomic uncertainty from three different socioeconomic scenarios (SSP1, 2 and 5) and climate uncertainty from varying climate sensitivity.

Results are shown in Figures 16 and 17, displaying carbon prices and emission pathways respectively. Clearly, the integration of damages leads to more ambitious near-term mitigation, increasing the gap between what is pledged under the current Nationally Determined Contributions (NDCs) and what is required under the optimal pathway in these scenarios in 2030 by two thirds compared to a pure cost-effectiveness approach. This requires higher carbon prices in the beginning but lower prices towards the end of the century as then less effort is needed to achieve the climate target. This leads to a flatter carbon price trajectory than in a cost-effectiveness analysis.

These results highlight the importance of integrating all relevant dimensions of climate change when informing climate policy decision makers, while missing adaptation, a key next research step.

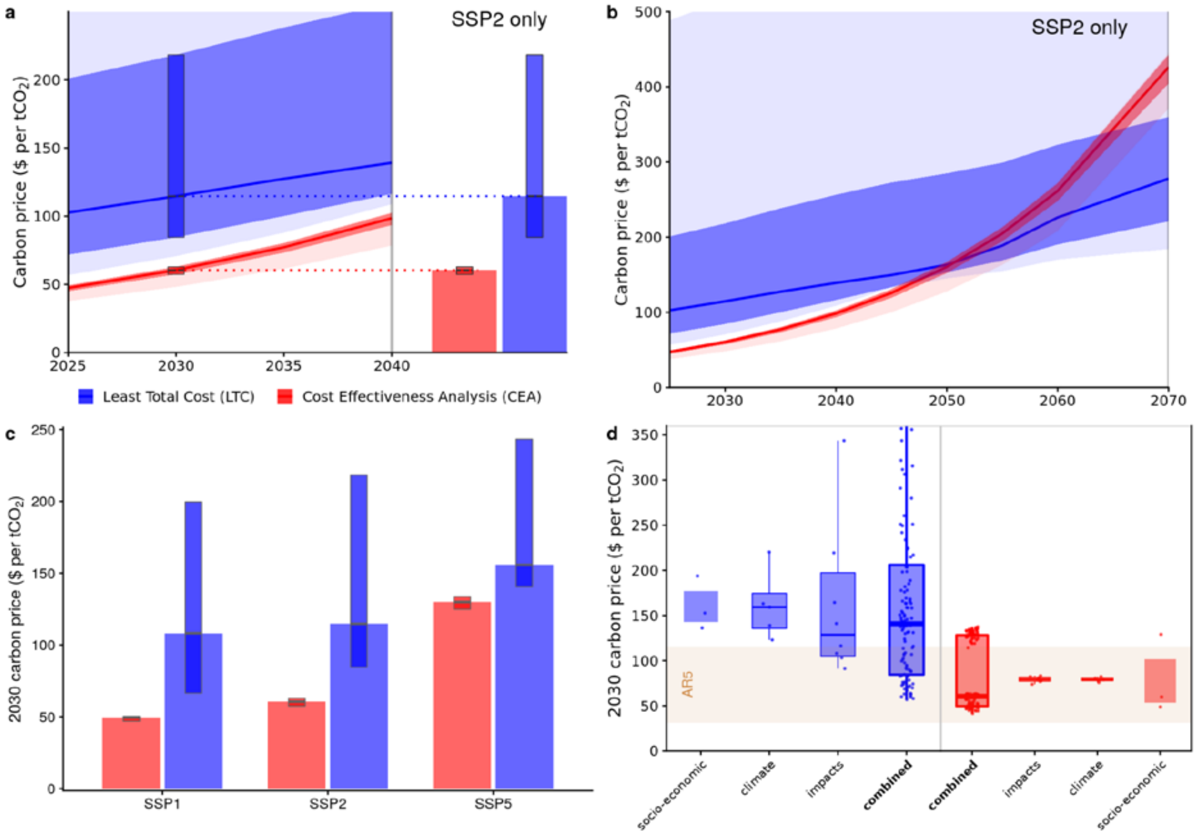

Figure 16 (taken from Schultes et al. 2021 Figure 4): Carbon prices for 2°C in welfare-optimal LTC pathways (blue) are higher in the near-term than for CEA (red). (a) Median carbon prices in 2030 are significantly higher for LTC than for CEA. The range in brackets are the 20th-80th percentiles across the scenario ensemble, also indicated in the dark ribbons in the plot; light ribbons are the min-max range. (b) Higher near-term carbon prcies of LTC are mirrored by lower prices from 2050 on; ribbons are as in (a). (c) Effect of different socio-economic baselines. (d) Uncertainty decomposition of the full ensemble into contributions of socio-economic baseline, climate and impact specification.

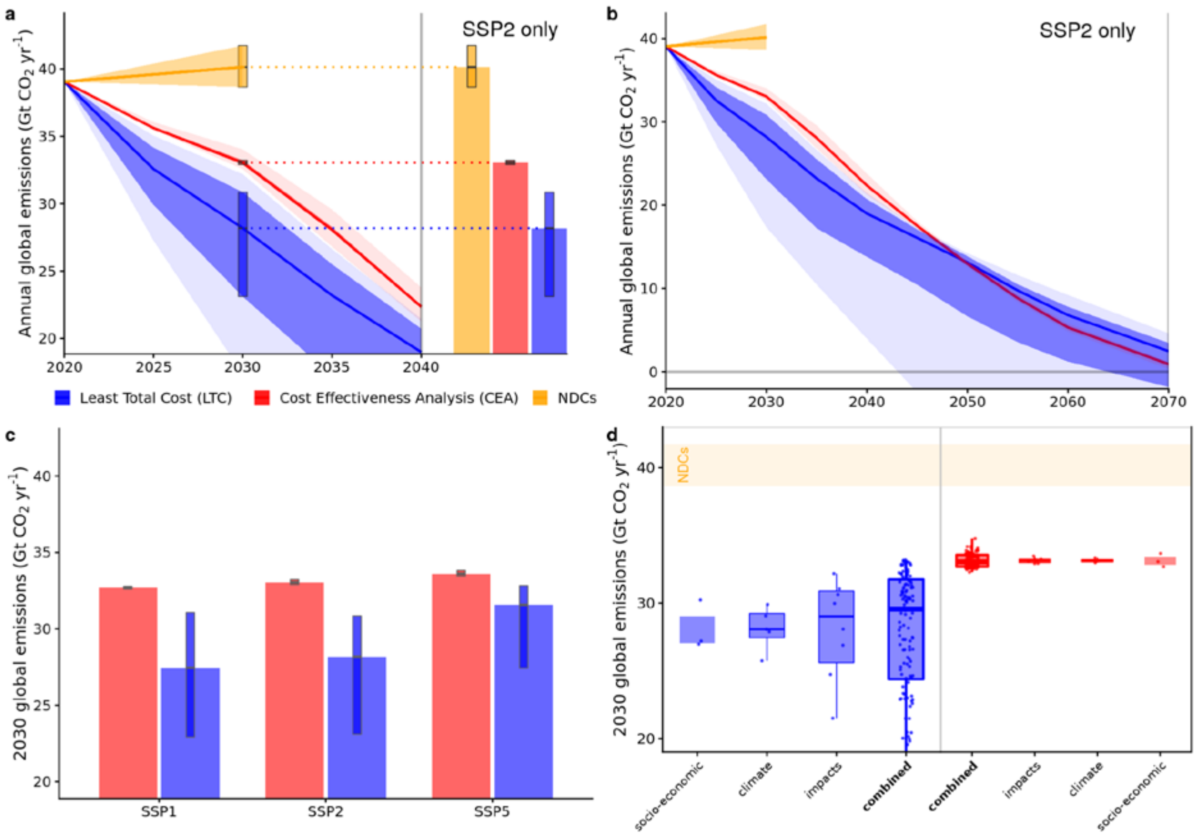

Figure 17 (taken from Schultes et al. 2021 Figure 5): Global CO2-only emissions for 2°C welfare optimal LTC pathways (blue) are below emissions for CEA (red) in the near term. Projections under the nationally determine contributions (NDCs) are included (yellow). (a) Median emissions in 2030 for LTC are significantly below those for CEA, increasing the gap to the NDCs. The range in brackets are the 20th-80th percentiles, also indicated in dark ribbons in the plot; light ribbons are the min-max range. (b) Lower near-term emissions of LTC are mirrored by higher emissions from 2050 on. (c) Effect of different socio-economic baselines on 2030 emissions. (d) Uncertainty decomposition of the full ensemble into contributions of socio-economic baseline, climate, and impact specifications.

3.3. Implementing other types of damages in REMIND

Building on the newly developed damage functions described above, we also extended the REMIND model to represent labor damages and tropical cyclone damages. Furthermore, we implemented an alternative aggregate macroeconomic damage function, published by Kalkuhl & Wenz (2020). Below, we describe these developments and example applications.

3.3.1. Kalkuhl & Wenz damages

Kalkuhl & Wenz (2020) improve upon the work by Burke et al. (2015) in two aspects: by using subnational GDP data from a newly developed database with data from 77 countries, and by building their empirical estimate on a comprehensive conceptual framework, allowing to test for all types of effects of temperature on economic growth. They find no evidence for long-term growth effects. Their preferred estimate is of the form $g_{i,t} = \alpha_1(T_{i,t} - T_{i,t-1}) + \alpha_2(T_{i,t-1} - T_{i,t-2}) + \beta_1(T_{i,t} - T_{i,t-1})T_{i,t-1} + \beta_2(T_{i,t-1} - T_{i,t-2})T_{i,t-1}$, where i denotes the country and t the year. Contrary to the finding of Burke et al. (2015), the change in the growth rate is driven by the annual change in temperature, not the level of temperature, meaning it does not persist beyond the initial temperature change. This leads to much smaller overall damages, albeit still larger ones than in damage functions typically used in cost-benefit IAMs (see Piontek et al. 2021).

3.3.2. Tropical cyclone damages

The damages from tropical cyclones can be treated as additive to empirically-based productivity damages, as the latter do not include damages from extreme weather events (see Kalkuhl & Wenz 2020). As the tropical cyclone (TC) damage function derived by Krichene et al. (in prep.) also affects economic growth, its implementation in REMIND is similar to Burke et al. or Kalkuhl & Wenz damages. The difference is that the latter is implemented on the level of REMIND regions (i.e. the damage function is driven by regional temperatures with damage coefficients being uniform for all countries/regions), whereas the TC damage function is driven by global mean temperature change, has country-specific coefficients and not all countries are affected. In terms of REMIND regions, MEA (Middle East and Northern Africa), NEU (non-EU European countries), REF (Reforming Economies) and EUR (Europe) do not have any TC impacts, the impacts on SSA (Sub-Saharan Africa) are tiny as only Madagaskar and Mozambique are exposed to TC effects.

Regional GDP per capita is given by $y_{r,t} = y_{r,t-1}\left(1 + g_{r,t} + \delta_{r,t}\right) = D_{r,t} Y_{r,t}^{gross}$ where $\delta_{r,t}$ is the damage effect and $D_{r,t} = \prod_{t'=t0}^{t}(1 + \delta_{r,t})$. For TCs $\delta_{c,t} = \beta_c^0 + \beta_c^1 T_t$, i.e. it is calculated on the country level. The total cumulative regional damage factor is then aggregated given each country's contribution to regional GDP $f_{c,t} = {Y_{c,t}^{gross}} \Big/ {Y_{r,t}^{gross}}$: $D_{r,t}^{TC} = \sum_c f_{c,t} D_{c,t}^{TC}$. For applications, we use the central estimate with 9 lag-years and the mean, 5th and 95th confidence interval across the historic growth response, climate, TC and socioeconomic uncertainties.

3.3.3. Labor damages

Contrary to the aggregate and TC damage functions, which reduce macroeconomic growth, labor is an explicit production factor in the REMIND model. Therefore, the impact on labor is implemented directly in the production function. As this is a productivity effect, it is already captured by aggregated functions like Kalkuhl & Wenz, therefore they cannot be applied together, otherwise there would be double counting of effects. We implement the labor supply damages as derived from Dasgupta et al. (2021, see above) as a level effect as follows: $Y_{r,t}^{net} = \left[\xi_{r,t}^K\left(\theta_{r,t}^K K_{r,t}\right)^\rho + \xi_{r,t}^E\left(\theta_{r,t}^E E_{r,t}\right)^\rho + \xi_{r,t}^L\left(\theta_{r,t}^L D^L(T_{r,t}) L_{r,t}\right)^\rho\right]^{1/\rho}$. Here, E and K are the other production factors energy and capital, ξ is the share and θ the efficiency parameter, and ρ is the calculated from the elasticity of substitution. Note that the REMIND model does not distinguish different labor sectors, therefore, a new regression using the Dasgupta approach and data was performed for REMIND regions and one overall labor effect (instead of distinguishing high and low exposure as in the original paper). The CAZ region, consisting mainly of Canada, Australia and New Zealand, is a very heterogeneous region for which the regression did not yield significant results. We therefore used the global regression results, which yields quite large positive effects which are likely an overestimation.

3.4. Results I – comparing different damage channels in baseline runs

We compare the effects of the different damage functions in REMIND baseline and cost-benefit settings. The baseline run uses the middle-of-the road SSP2 socioeconomic scenario, with emissions leading to a 3.5°C temperature increase above pre-industrial by 2100. Figure 18 shows total global GDP loss in 2100 due to damages, compared to a no-damage baseline case for different types of damages. The central cases of our analysis are the Kalkuhl & Wenz (KW) damage function, the labor and tropical cyclone damages (TC). Note that for the latter we apply a high, medium and low damage, given by the 17th and 83rd percentile and the mean across the uncertainty range as described above. We also show the combined effect of tropical cyclone and aggregate output KW damages, as well as results with the Burke damage function with limited (15 year) and infinite persistence, building on the work in Schultes et al. (section …). These high persistence cases lead to much higher damages than all other variants. Tropical cyclone damages increase the global loss by almost 25% compared to pure KW damages, while labor makes up 75% of the global loss captured in KW, which is quite substantial.

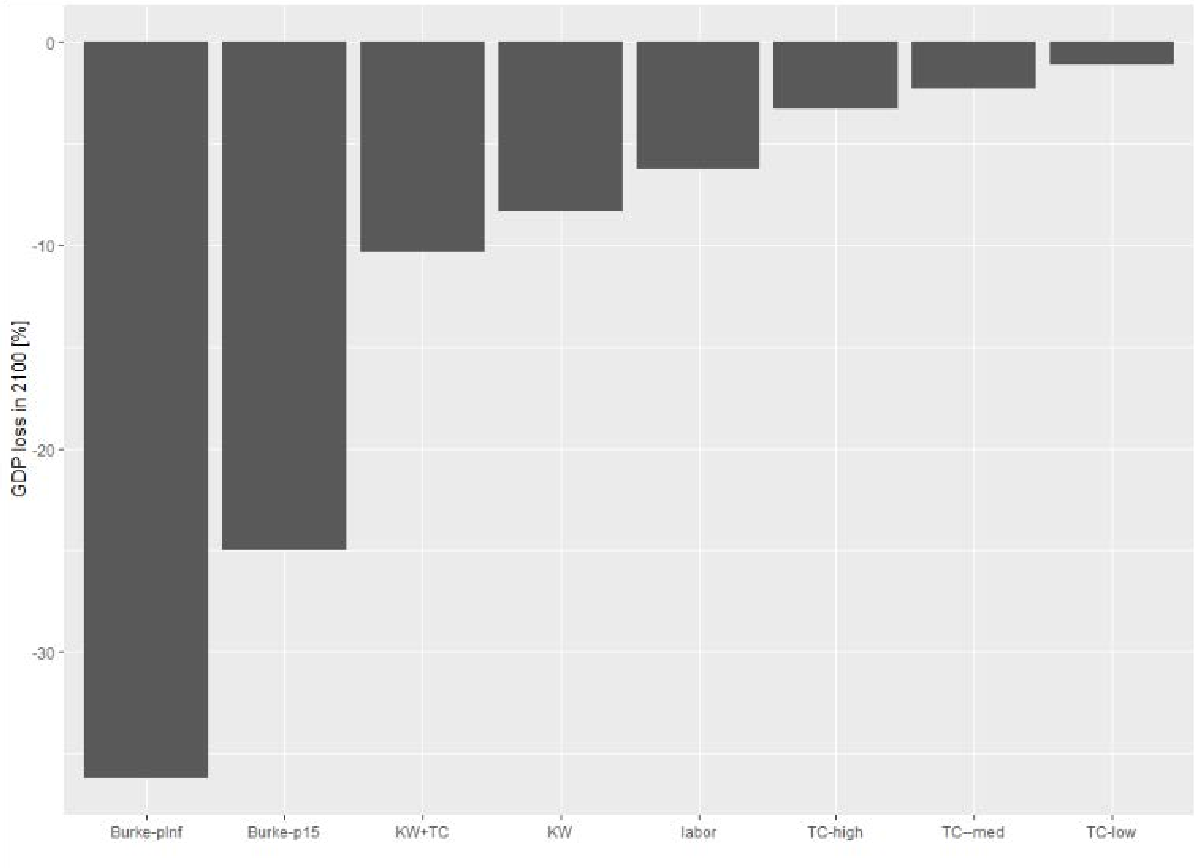

Figure 18: Total global GDP loss in 2100 due to damages (compared to a no-damage baseline), compared to a no-damage baseline case for different types of damages, from left to right: Burke-pinf = aggregate damage function from Burke et al. (2015) with infinite persistence, Burke-p15 = aggregate damage function from Burke et al. (2015) with 15 years half-life time, KW+TC = aggregate damage function from Kalkuhl & Wenz (2020) combined with damages from tropical cyclones based on Krichene et al. (2022), KW = damage function from Kalkuhl & Wenz (2020), labor = damages on labor supply based on Dasgupta et al. (2021), TC-high/med/low = damages from tropical cyclones based on Krichene et al. (2022) capturing the range of uncertainty from low to high damages.

Figure 19 shows the associated damage factors (defined by $D_{r,t} = {Y_{r,t}^{net}}/{Y_{r,t}^{gross}}$ for the different types of damages for the 12 world regions, comparing labor effects, TC impacts and aggregate output effects based on Kalkuhl & Wenz ("KW"). TC effects are strongest by far in Japan, stronger than any impacts of the estimates used here and stronger than the aggregate KW damage function, reducing GDP by about 13% in 2100 for the medium TC damage estimate. Also, for OAS (which includes strongly TC-prone countries like the Philippines or Vietnam) and the USA TC effects are significant. Labor impacts are strong in Europe or India, where they are essentially on par with the aggregate KW impacts, or in NEU, where the effect is even larger. In other regions, the labor component is only a fraction of the KW effect, e.g. in the USA, or positive (REF, CAZ, though see the notes on CAZ above). As labor effects should be captured by the aggregate damage function, this comparison emphasizes the challenge of understanding better which channels make up the aggregate damages.

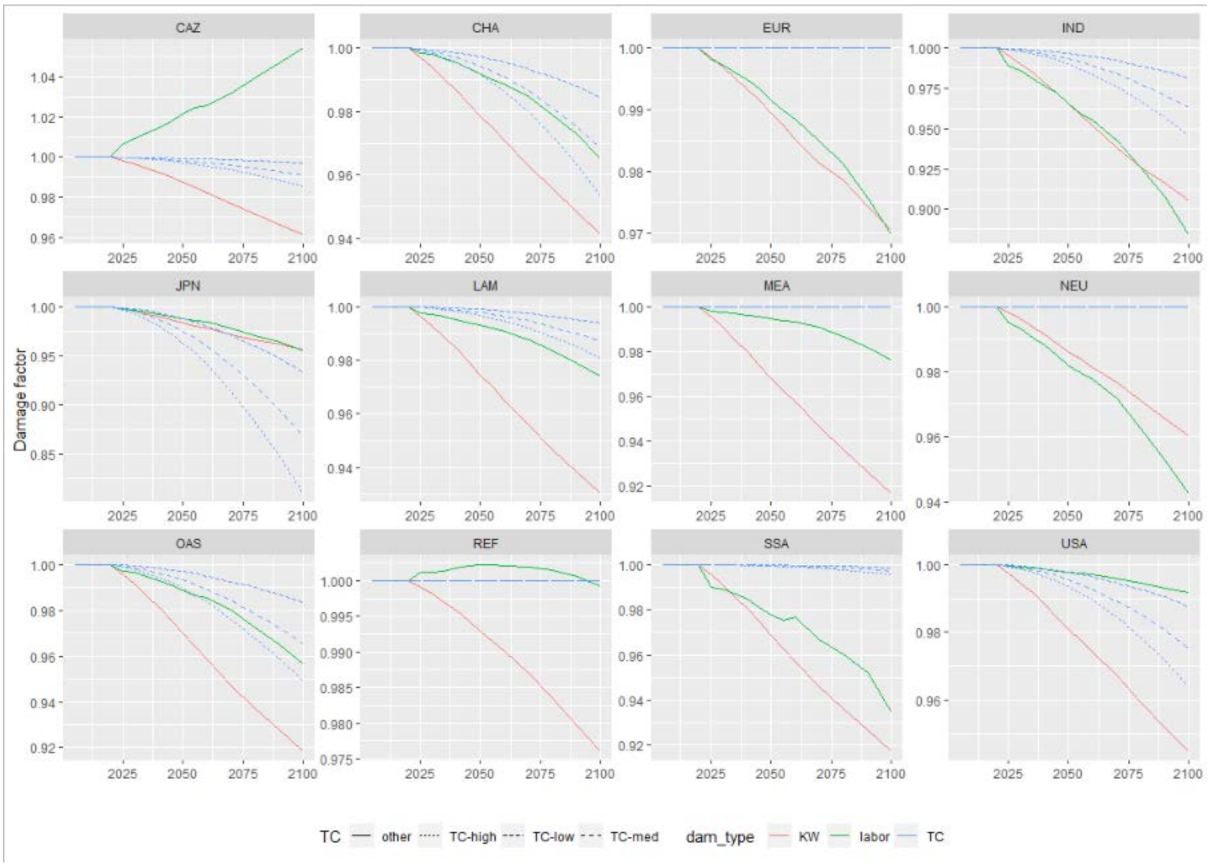

Figure 19: Regional damage factors for the 12 REMIND regions and different types of damages. Colors = type of damages (KW = aggregate damages from Kalkuhl & Wenz (2020), labor = labor supply from Dasgupta et al. (2021), TC = tropical cyclone damages from Krichene et al. (2022)), line style = range of different magnitudes for tropical cyclone damages.

As we apply the damages in a growth model we can distinguish between direct damages, given by the damage function determined by temperature changes, and indirect damages, e.g. resulting from changes in savings rates (Piontek et al. 2019). Figure 20 distinguishes these two components of the overall GDP change. Note that for TC damages, the regions which are not affected directly by tropical cyclones (EUR, NEU, REF and MEA) are affected indirectly through trade effects, with small positive effects for the latter three. For labor the indirect effects are stronger than the direct effects, as the savings rate responds differently than to the output damages. This is illustrated in panel b of Figure 20, showing that the change in the global macroeconomic investment is similar in the case of labor and KW damages, even though the GDP loss is smaller, in turn reflected in less consumption loss for labor damage. These different dynamic effects highlight the importance of actually using a growth model rather than ex-post application of damage functions to evaluate impacts

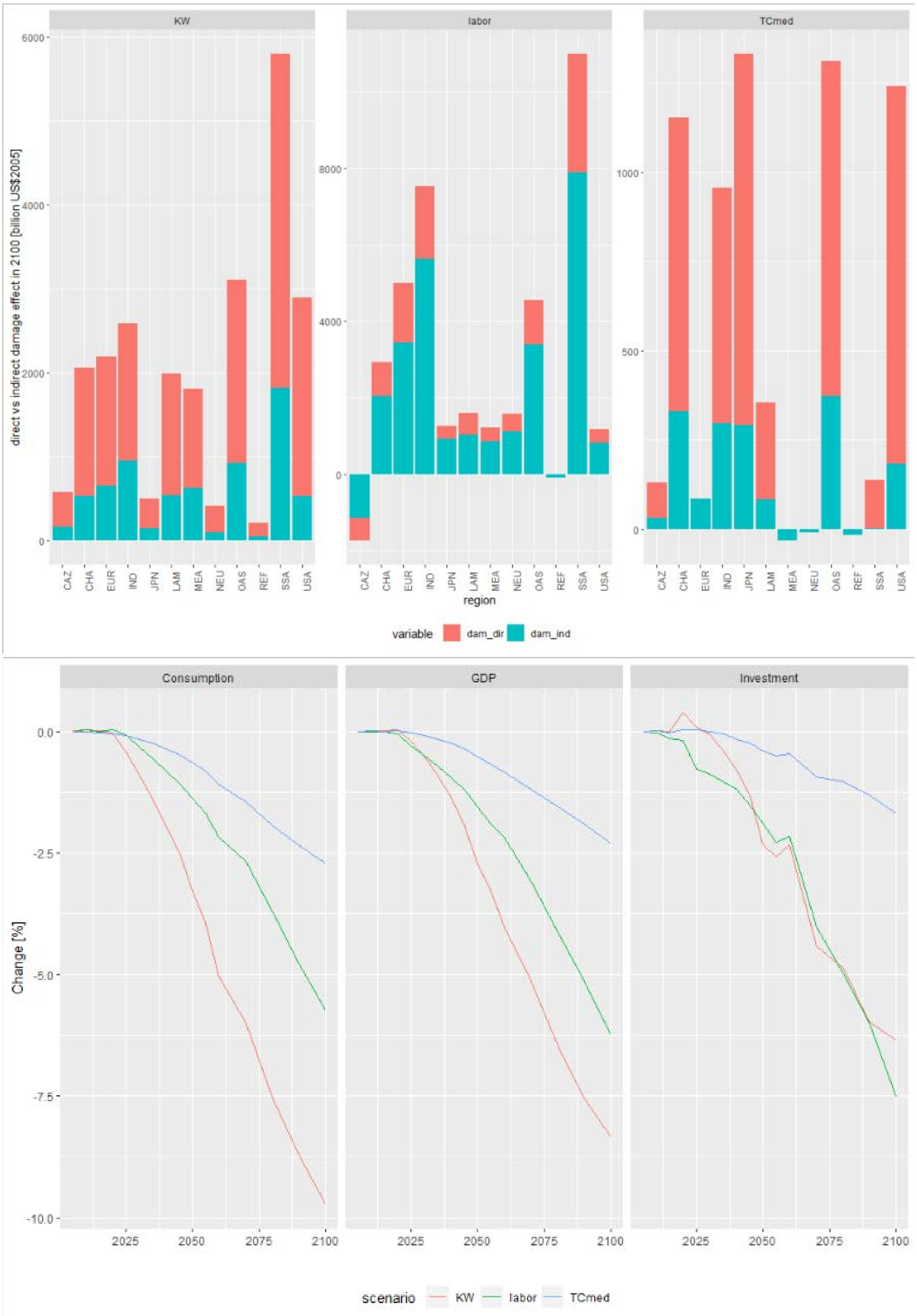

Figure 20: Top panel: Decomposition of total GDP loss into direct (red) and indirect (turquoise) effects for different types of damages (from left to right: KW = aggregate damages from Kalkuhl & Wenz (2020), labor = labor supply damages from Dasgupta et al. (2021), TC-med = median damages from tropical cyclones from Krichene et al. (2022). Bottom panel:

Changes in consumption, GDP and investment for the different types of damages (red = aggregate damages from Kalkuhl & Wenz (2020), green = labor supply damages from Dasgupta et al. (2021), blue = median damages from tropical cyclones from Krichene et al. (2022)).

3.5. Results II – cost-benefit analyses

In a cost-benefit setting, damages are internalized via a carbon tax made up of the social cost of carbon as described above. We use a cost-benefit setting to illustrate the policy effects of the different damage channels and functions, however, the resulting pathways should not be considered an optimal response to climate change as many types of impacts are still missing in this assessment.

Figure 21 shows the resulting emission, carbon tax and global mean temperature pathways. All of the damage functions and channels investigated yield temperature increases of above 2° by the end of the century in this optimal setting, with the exception of the persistent Burke-based damage functions. While tropical cyclone damages alone somewhat stabilize emissions but still lead to temperature increases of almost 3°, labor damages alone yield a clear emission reduction towards the end of the century, though with a stagnation phase in the middle. Combining TC damages with aggregate KW damages yields a further decrease in end-of-century temperature by 0.1°. The globally uniform carbon tax derived from the social cost of carbon of the damages in 2030 ranges from 5.3 US$/t CO2 from tropical cyclone damages alone (medium estimate) to 31.5 US$/t CO2 for the combination of aggregate KW and TC damages. It is significantly higher for the Burke-based damages.

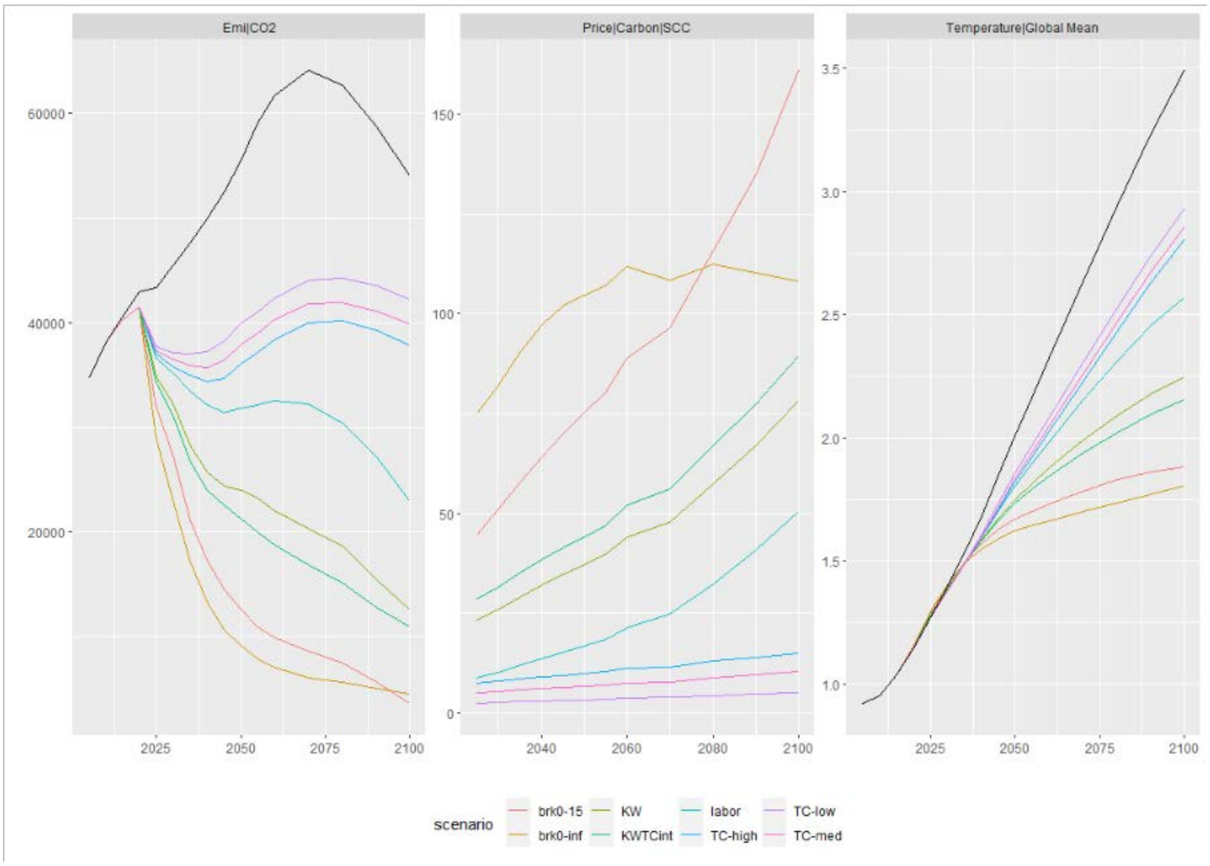

Figure 21: Cost-optimal emission, carbon price and temperature pathways (from left to right) for the different types of damages (colors). Black indicates the no-damage baseline. Emissions are CO2 only, measured in Mt CO2/year. The carbon price is in US$2005 and temperature increase is in °C above pre-industrial. Damages: orange (brk0-inf) = aggregate damage function from Burke et al. (2015) with infinite persistence, red (brk0-15) = aggregate damage function from Burke et al. (2015) with 15 years half-life time, green (KWTCint) = aggregate damage function from Kalkuhl & Wenz (2020) combined with damages from tropical cyclones based on Krichene et al. (2022), olive (KW) = damage function from Kalkuhl & Wenz (2020), turquoise (labor) = damages on labor supply based on Dasgupta et al. (2021), blue/purple/pink (TC-high/med/low)

= damages from tropical cyclones based on Krichene et al. (2022) capturing the range of uncertainty from low to high damages.

For individual regions we can look at the costs, benefits and residual damages, displayed in Figure 22. Several things can be noted. First, contrary to simple cost-benefit IAMs with mitigation cost functions, it is not straight-forward to determine mitigation costs for a process-based IAM where mitigation means complex changes in the energy system. Here, costs are defined as the difference between the GDP in the baseline run without damages and the GDP before damages of the CBA run ("Y_gross"). However, as discussed in the previous section, Y_gross includes the indirect effects of the damages, rendering this somewhat imprecise. This also leads to positive "costs" in some regions which actually benefit from climate change impacts or, in the case of tropical cyclones, are not directly affected themselves. Furthermore, depending on the region, residual damages can be quite substantial. This highlights the need to advance the assessment to include adaptation and associated costs and benefits to capture the full range of policy options. Benefit-cost ratios are generally lower in India (around 2) and fairly high in CHA, LAM, NEU, OAS and USA (6 to over 15 in some cases), with the other regions in between. The different savings rates dynamics for the damage types already discussed for the baseline results also occur here, illustrated in Figure 23. In particular, the tropical cyclone damages induce higher savings rates in the beginning, compared to the labor channel.

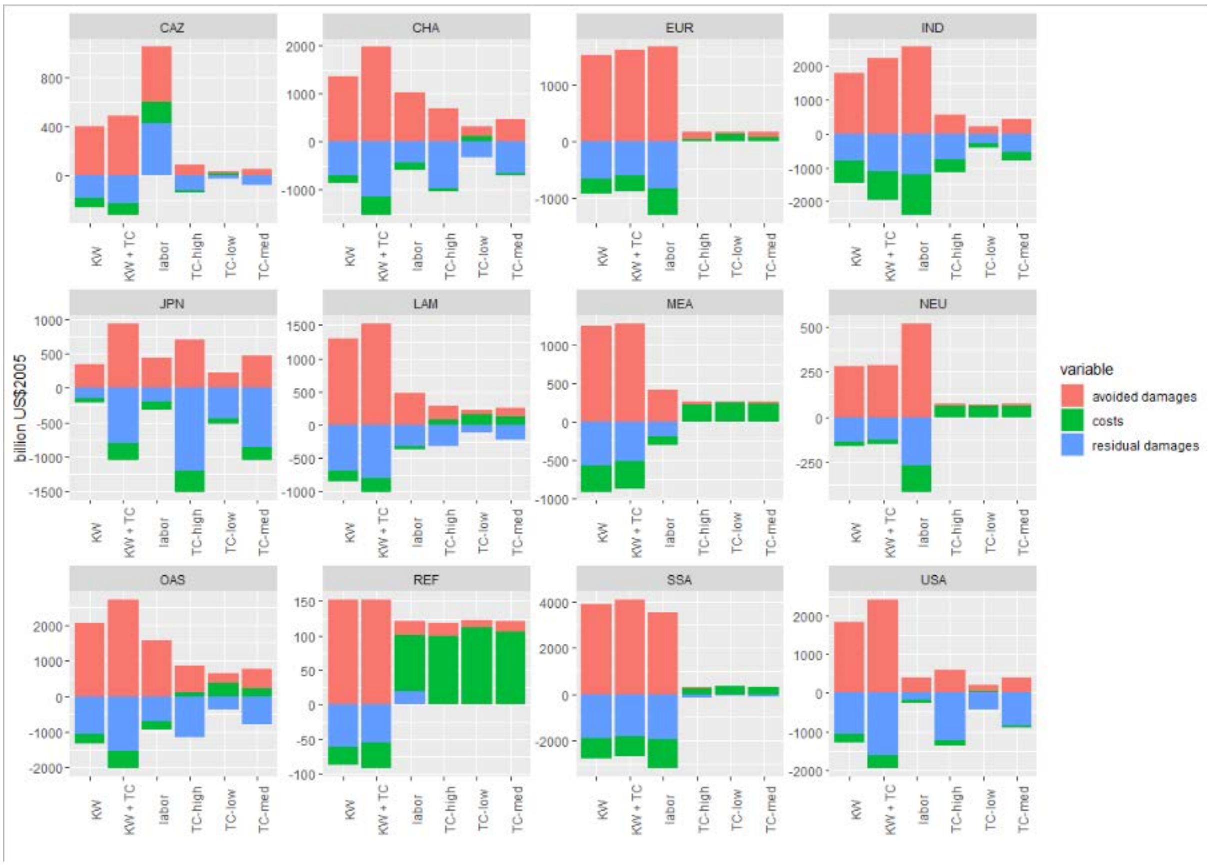

Figure 22: Decomposition into avoided damages (red), residual damages (blue) and policy costs (green) for the cost-optimal pathways in 2100. Positive policy costs stem either from positive climate impacts (e.g. for labor effects in cooler regions like REF) or for regions without damages from tropical cyclones (e.g. EUR, NEU, REF, SSA). The different bars are for different damage functions: KW = aggregate damages from Kalkuhl & Wenz (2020), KW+TC = combination of aggregate damages from Kalkuhl & Wenz (2020) and median tropical cyclone damages from Krichene et al. (2022), labor = labor supply damages from Dasgupta et al. (2021), TC-high/med/low = high/median/low damages from tropical cyclones from Krichene et al. (2022).

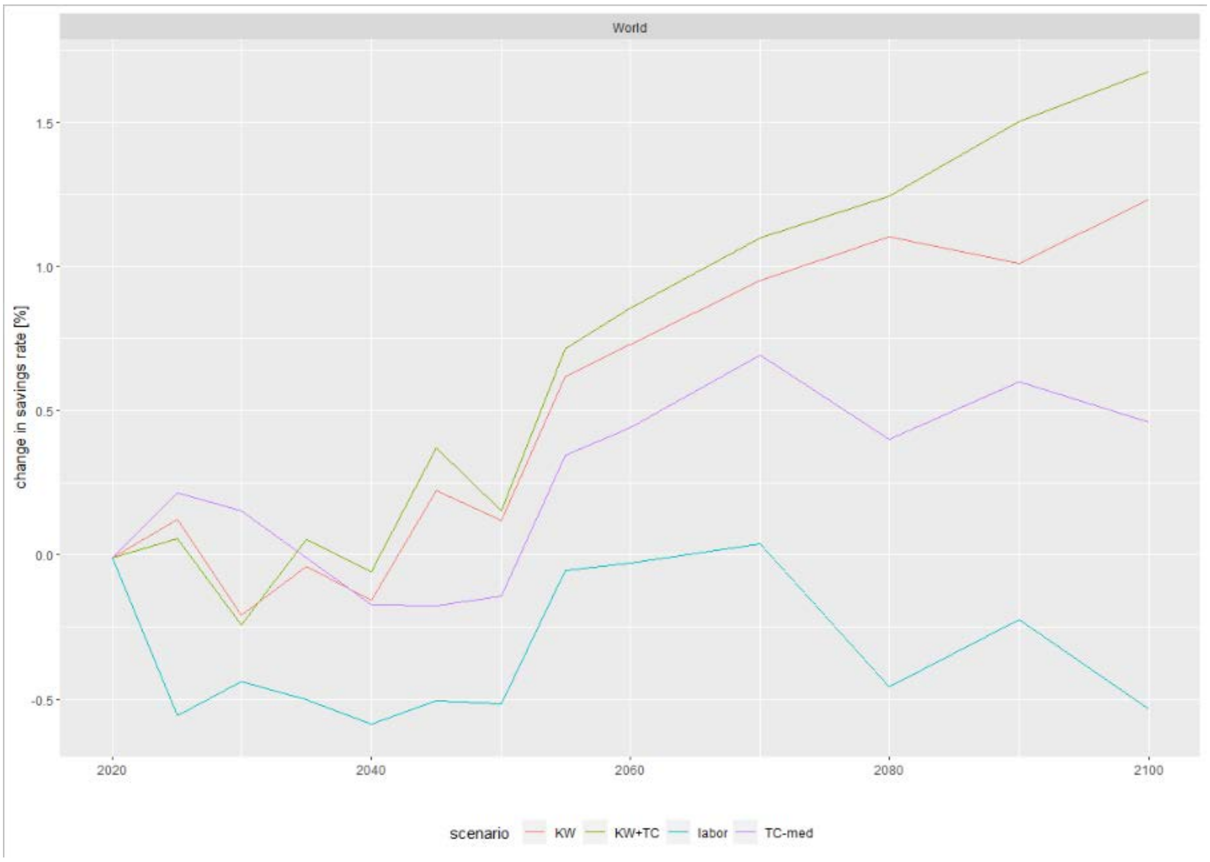

Figure 23: Change in the savings rate over time in the cost-optimal scenario for different damage functions compared to the baseline without damages. Red (KW) = aggregate damages from Kalkuhl & Wenz (2020), olive (KW+TC) = combination of aggregate damages from Kalkuhl & Wenz (2020) and median tropical cyclone damages from Krichene et al. (2022), blue (labor) = labor supply damages from Dasgupta et al. (2021), purple (TC-med) = median damages from tropical cyclones from Krichene et al. (2022).

4. Links to other CHIPS work and future research

The advancements in the economic damage estimates of climate change will be used in other parts of the CHIPS project. For tropical cyclones two further studies are under way. The first aims to estimate the differentiated effects of tropical cyclones across different income regions and, building on that, on different income groups in the population. First results show that accounting for this inequality improves the agreement of model-based TC risks with nationally reported TC damages, highlighting the importance of including this. Furthermore, this will allow to link it to assessments of future inequality effects related to climate change. The second study plans to use the TC damage estimates in country-level study for Mexico, applying the microsimulation model developed in CHIPS work package 3. The model will be calibrated to study the distributional effects of hurricane Manuel, hitting Mexico in September 2013 and causing damages of around US$4.2 billion. Using approaches from the ISIMIP project in conjunction with the empirical TC damage results we can then (i) attribute the damages of hurricane Manuel to climate change and assess the contribution of present-day climate change to its distributional effects; (ii) use projections to estimate the strength of a typical hurricane affecting Mexico under future climate change and compare its results to those of Manuel, thereby assessing future adaptation needs in Mexico.

In work package 4 the aggregate economic damage functions will be linked to the representation of household heterogeneity in the REMIND model with the goal to study distributional effects of both climate policy and climate damages within the REMIND integrated assessment system.

Future work will need to advance the damage representation in the REMIND model to improve the ability to capture further channel-specific damages, in particular damages on capital, as well as damages not available in the form of a temperature-dependent damage function. The question of persistence of damages will need to be investigated further, both from an empirical and a modeling angle. Finally, adaptation will need to be introduced in the model, requiring better estimates of its costs and effects on a disaggregate and aggregate level.

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