A multi-agent approach for climate change negotiations

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A MULTI-AGENT APPROACH FOR CLIMATE CHANGE NEGOTIATIONS

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Dedicated to Giulia and Anna.

Abstract

Climate change has become the most relevant, complex and challenging problem of mankind in present times. It affects all countries around the planet yet in many different ways. The high level of heterogeneity of impacts complicates the evaluation of the best policies and mitigation strategies to be implemented by the different nations. Moreover, regional inequality further exacerbates the international negotiation and coordination process.

The available benefit-cost optimizing Integrated Assessment Models — among the most influential models that climate scientists and economists use to assess optimal policies and inform policymakers — are relatively limited in the representation of spatial heterogeneity. This is despite strong evidence of significant regional variation of mitigation costs and benefits, institutional capacity, environmental and economic priorities. At the same time, a more flexible framework to investigate the complex behaviours and distributed decision-making dynamics that emerge from international negotiations for climate agreements is strongly needed.

This doctoral dissertation first contributes to the advancing of regional calibration in benefit-cost Integrated Assessment Models. It adopts the most recent scientific empirical contributions as sources of heterogeneity of climate change impacts and mitigation costs. Then, it discusses new assessments on optimal mitigation-policy responses, principally focusing on the inequality implications across regions. Last, it formalizes a novel agent-based negotiation framework, as a flexible approach to account for the different perceptions and decision forces in international climate negotiations.

This contribution aims at providing new tools and useful insights to both academics and policymakers, to better understand how heterogeneity affects climate change mitigation policies. It also contributes to better modelling the decision-driving forces in a complex and distributed setting like the climate change international negotiation, eventually supporting the strenuous diplomatic action in the search for cooperation-enabling arguments.

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Success is best when it is shared.
— Howard Schultz

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Chapter

1 Overview

1.1 Research context

Climate change has become the most relevant, complex and challenging problem of mankind in present times. It affects all countries around the planet yet in heterogeneous ways. The Intergovernmental Panel on Climate Change (IPCC), the United Nations body for assessing the science related to climate change, periodically releases reports, results of a rigorous peer-reviewing process. Its last Fifth Assessment Report (AR5)[1] unequivocally appraise how the rising concentrations of carbon dioxide (CO2) and other greenhouse gases (GHG) in the atmosphere are leading the world towards an alarmingly fast Global Mean Temperature (GMT) increase (IPCC, 2014). It estimates the human responsibility as the *extremely likely* predominant cause of the phenomenon, that is with a confidence level greater than 95%. Without fast and coordinated efforts to cut GHG emissions and reach at least a net-zero balance, climate change would lead both natural and human systems to unprecedented —and likely catastrophic— scenarios. For example, Carleton and Hsiang (2016) provide an extensive review of the most significant climate repercussions that potentially affect economies and societies. They include straight consequences on human health, economic impacts on GDP production, energy and trade, influence on social interactions, and a significant contribution to mass migrations and other high-scale demographic effects.

Any adequate action and policy must necessarily rely on joint international emissions-mitigative efforts and, therefore, on a strong level of cooperation among nations. The AR5 Report, again, explicitly states that *effective mitigation [of greenhouse gases] will not be achieved if individual agents advance their own interests independently* (IPCC, 2014). An assertion reiterated and strengthened in the more recent Special Report (IPCC, 2018) which focuses on strategies to keep GMT increase below 1.5°C by the end of this century. The United Framework Convention on Climate Change (UNFCCC) plays a key role in the diplomatic process. The yearly-scheduled Conference Of the

[1] During the final days of revision of this thesis, the IPCC released the Working Group I contribution to the Sixth Assessment Report (AR6). It addresses the most up-to-date physical understanding of the climate system and climate change (see https://www.ipcc.ch/report/ar6/wg1/). Despite not being explicitly accounted for in this thesis, it confirms all reported claims with an even higher level of concern for future scenarios.

Parties (COP) meetings have unquestionably taken many steps forward in communicating the high risks and in their attempt to reduce divergences and find room for shared agreements (Dimitrov, 2015; Gupta, 2012). On the other hand, since the very beginning of the negotiation process, the debate has quickly expanded, including all the most significant global issues: north-south inequality, international financing, technology transfer and economic growth (Hecht and Tirpak, 1995). Over the last decade, many coalitions have changed, new alliances have emerged, and the bargaining process itself has moved from a top-down approach (Dimitrov, 2010) to a bottom-up, voluntary-based one (Stewart, Oppenheimer and Rudyk, 2013). The Paris Agreement (COP21), in December 2015, marked one of the most important milestones so far (UNFCCC, 2015). The merit was attributed to the flexible approach adopted, based on building blocks called (Intended) Nationally Determined Contributions (INDCs, then become NDCs), which helped in building a solid ground for the treaty acceptance (Dimitrov, 2016). However, as already pointed out by several contributions (e.g., see Rogelj et al., 2016; Höhne et al., 2017), current pledges are largely insufficient to meet the ambitious target of keeping global temperature increase *well below 2°C, preferably to 1.5°C compared to pre-industrial levels* by the end of this century (UNFCCC, 2015).

Despite an increased awareness of the potential risks and the urgency of actions, any stable and ambitious coordination on responsibilities, efforts, and policies seems still far from being achieved. The strongest obstacle is certainly the public-good nature of the climate change problem, and the consequent underlying incentive to act as free-rider (Hoel, 1991). Countries, in fact, are always strategically encouraged to rely on emission reductions done by the others instead of undertaking personal efforts (e.g., see Nordhaus, 2010; Bosetti, Carraro, De Cian et al., 2013; Nordhaus, 2015). The resulting outcome is called *tragedy of the commons* (Hardin, 1968), a scenario where each agent has no rational incentive to deviate from its selfish behaviour, getting the benefits of a public good without contributing to its costs. Free-riding is, therefore, a force that can anytime cause failures in international treaties and undermine the essential mutual trust among nations (Gupta, 2012). For a notable historical example, see how the Kyoto Protocol (COP3) has been remarkably weakened after the U.S., Canada, Australia, Japan, and Russia stepped away in 2001 (Clémençon, 2016). Consequently, the Paris Agreement itself, despite being one of the most promising treaties the parties ever signed, is exposed to a weakening risk of unilateral withdrawals as well. The U.S. recently demonstrated that sudden turnarounds are a real possibility (for example, as a direct consequence of flipping results in political elections). And, unfortunately, a handful of main emitters have a predominant responsibility in the global carbon balance, so that they cannot be left out from any international treaty without undermining its effectiveness (Bosetti, Carraro, De Cian et al., 2013; Lessmann et al., 2015).

Among the different models that climate scientists and economists use to inform policymakers on mitigative actions, the Integrated Assessment Models (IAM) play an influential role (e.g., see Weyant, 2017; Weyant, 2014; Weyant et al., 1996; Nordhaus and Boyer, 2000). They are called *integrated* due to the different subject areas — economy, energy and climate — that are interconnected within a common framework. Despite some necessary simplifications and modelling assumptions, *integrated assessments provide a sense of the relative* *importance of different factors, highlight those of greatest importance, and help policymakers focus on the tradeoffs involved* (CBO Congressional Budget Office, 2003). They have been largely used to investigate complex and long-term interactions between human development and the natural environment, to get insights on potential economic impacts, estimate policies effectiveness and costs (also called CEA, cost-effective analysis), and assess optimal mitigation pathways (also called CBA, cost-benefit analysis) for different scenarios.

Weyant (2017) classifies IAMs into two main categories: *detailed process* (DP) and *benefit-cost* (BC) models. The DP-IAMs provide more information as they include economic sectors, a high degree of geographical disaggregation and a more complex system for physical impacts and feedbacks. Their main usages include mitigation analysis (i.e., projections of mitigation costs under a variety of specific assumptions), climate impact analysis (i.e., climate change consequences on agriculture, water, biodiversity and economic sectors), and integrated mitigation and impact analysis (i.e., interactions between impact sectors under mitigation and adaptation policies). Some notable (non-exhaustive) examples for DP-IAMs are: MESSAGE (Huppmann et al., 2019), IMAGE (Stehfest et al., 2014), MERGE (Blanford et al., 2013), TIAM-ECM (Keppo and van der Zwaan, 2012), REMIND (Aboumahboub et al., 2020).
The BC-IAMs, on the other hand, aggregate the physical impacts and economic costs of climate change and the benefits of GHG emissions mitigation. These models have been extensively adopted to assess the optimal trajectory of global GHG emissions (i.e., those balancing the marginal cost against the marginal damages resulting from the last ton emitted) and the corresponding policy-equivalent prices to charge for those emissions (see also: Weyant, 2014). Moreover, they have been used to estimate the additional costs of nonoptimal climate policies and evaluate the social cost of carbon (SCC), which is the marginal damage caused by an additional ton of carbon emissions. Their main dynamics can be calibrated upon the more detailed estimates and projections of DP-IAMs. Among BC integrated models, significant and actively adopted examples are: DICE (Nordhaus, 2008), RICE (Nordhaus and Yang, 1996), FUND (Anthoff, 2009), PAGE (Hope, 2008).
Moreover, there also exist some so-called *Hybrid* models, which are top-down IAMs with an additional level of endogenous detail on specific sectors or dynamics. They can usually perform both Benefit-Cost optimizations and Cost-Effective Analyses. Notable examples for this category are: WITCH (Bosetti, Carraro, Galeotti et al., 2006) and DEMETER (Gerlagh et al., 2004).

When accounting for the distributed decision-making essence of the mitigation problem, IAMs have been often combined or sided by game theory models. In particular, BC optimizing models characterized by multiple regions usually perform both cooperative (social welfare maximization) and non-cooperative (Nash equilibrium) assessments (e.g., see Bosetti, Carraro, Galeotti et al., 2006). In addition, several studies have adopted IAMs also to investigate the problems of coalitions formation and agreement stability. Notable contributions on these topics are Carraro and Siniscalco (1992) and Carraro and Siniscalco (1993), Barrett (1994) and Barrett (2001), Bosetti, Carraro, De Cian et al. (2013), Nordhaus (2015) and Lessmann et al. (2015). On the other hand, other studies have adopted game theory to investigate International Environmental Agreements (IEA), implementing custom and more specific multi-player settings. See in particular the contributions addressing IEAs stability (e.g., see Battaglini and Harstad, 2016; Bayramoglu, Finus and Jacques, 2018; Biancardi and Villani, 2014), cooperation incentives (e.g., see Cole, 2011; Schwerhoff et al., 2018) or optimal transfers (e.g., see McGinty, 2007). Refer also to McGinty (2020) for an updated review on this field.

The contribution of this doctoral thesis comes at the intersections of the presented topics. It addresses the needing for a better representation of the regional heterogeneities in BC-IAMs and the estimation of the consequent effects on benefit-cost scenarios and cooperation strategies. It also proposes a new Agent-Based modelling approach to account for the different perceptions and decision forces that take place in IEA negotiations.

1.2 Research objectives

Modelling research has achieved remarkable advancements in IAMs and in their efficacy for policy advice; however, there remain several improvement directions. Weyant (2017) identifies the following main challenges for advancing the design and use of IAMs: (1) a wise selection of mitigation options and climate change impacts and an accurate; (2) the inclusion of potentially catastrophic climate changes and consequent extreme impacts in the models' dynamics; (3) the treatment of regional, national, and international equity, as well as an improved assessment of impacts across income classes at the national or international level; (4) the treatment of intertemporal discounting and intergenerational equity, especially in BC-IAMs trade-offs; (5) projections over a satisfactory range of baseline drivers; (6) capturing interactions between impact sectors and feedbacks to the climate system, like the exacerbated competition for natural resources; last but not least, (7) dealing with deep uncertainty and risk in distributed ad sequential decision-making.

This thesis addresses the key aspects of improving the heterogeneity representation of mitigation costs and damages in BC-IAMs to the latest science. It investigates the consequent optimal-policy assessments under a wide range of different scenarios, with a specific focus on international equity. In fact, popular benefit-cost optimizing models like RICE (Nordhaus, 2010; Nordhaus and Yang, 1996), PAGE (Hope, 2008), FUND (Anthoff, 2009), C^3IAM(Wei et al., 2020), CWS (Eyckmans and Tulkens, 2003), WITCH (Bosetti, Carraro, Galeotti et al., 2006), MICA (Lessmann et al., 2015), and STACO (Nagashima et al., 2009), execute only from 6 to 16 independently deciding regions. This resolution allows only partially to capture the variation in the costs and benefits of climate action. And therefore, it provides limited insights on the different optimal strategic positions that constitute the international negotiation and distributed decision-making context.

Furthermore, also traditional approaches for modelling the international negotiation setting — i.e., based on game theory— show significant limitations because of these complex and highly heterogeneous dynamics. As extensively discussed by Finus (2008), researchers and policymakers need more flexible tools to simulate multiple and distributed decision-making scenarios, also on the basis of subjective and non-material payoffs, differentiated geopolitical strategies, and ethical perspectives (see also: Konrad and Thum, 2014; McGinty, 2007; Schwerhoff et al., 2018).

This thesis first brings about the enabling bases for optimal policies assessment by calibrating a regional IAM that properly accounts for the heterogeneity of costs and damages; hence it proposes a new framework to reproduce and investigate international negotiations on greenhouse gases emissions regulation. This simulation model follows an Agent-Based approach, starting from the strategic behaviour of each region-representative negotiator (informed by benefit-cost optimal projections). Indeed, as discussed again by Finus (2008), despite the undeniable presence of coalitions, alliances and mutual objectives, any final decision in international treaty signing and real action-taking is always up to every single sovereign nation.

1.3 Research structure

This doctoral dissertation consists of three main contributions. At first, it provides the definition and calibration of RICE50+, a Benefit-Cost optimizing IAM with more than 50 independently-deciding representative agents.
Then, it follows an extensive analysis of the benefit-cost assessments projected by the model. Results depict optimal policies and their consequences under a wide range of assumptions on socioeconomic development, climate impacts, and preferences over time and inequality. It confirms the importance of cooperation to meet the Paris targets and points out a critical persistence of economic inequality exacerbated by climate damages.
Last, it defines a new agent-based negotiation framework, a novel approach to investigate the complex and distributed decision-making processes of international negotiation on greenhouse gases reductions. This tool is coupled with RICE50+ model dynamics and informed by its optimal benefit-cost assessments data.

Each contribution of this thesis addresses a specific research question within the framed context described so far and consists of consolidated material that has already reached or is currently targeting publication in high-quality scientific journals. Here follows a brief overview for each of them.

1.4 Paper 1 - RICE50+: DICE at (almost) country level

Research questions

The first contribution of this thesis aims at improving the representation of spatial heterogeneity for mitigation costs and climate change impacts in benefit-cost policy-optimizing modeling. It defines a new regional IAM, called RICE50+, which originates from the well-known Nordhaus' DICE and RICE core foundations (e.g., see Nordhaus, 2018). It provides an extensive description of all the modelling choices made for its proper calibration.

It pursues the following main research question:

RQ 1. *How can benefit-cost policy-optimizing Integrated Assessment Models be effectively improved, following the latest science, data availability, and properly accounting for regional heterogeneity?*

Related and more specific sub-questions are the following:

RQ 1.1. *Do regional heterogeneities play a big role in top-down general-equilibrium model outcomes?*

RQ 1.2. *How can we properly integrate some recent and robust empirical findings on climate change impacts (i.e., Burke, Hsiang and Miguel, 2015; Dell, Jones and Olken, 2012; Kahn et al., 2019) in Benefit-Cost IAMs?*

RQ 1.3. *How can we account for different preferences on regional inequality in an integrated model welfare function?*

Methodology

The methodology adopted here lays in the field of traditional Integrated Assessment modelling. We defined RICE50+ as a Ramsey-type optimal-growth model that inherits the core scaffold from the most-updated DICE-model definition (i.e., DICE2016-R2; see: Nordhaus, 2018). We introduced 57 independently deciding regions according to the finest granularity data available for mitigation costs. Exogenous population and GDP output can follow five alternative and consistent socioeconomic scenarios (the so-called SSPs; e.g., see O'Neill et al., 2014; Riahi et al., 2017).
A significant step forward consists of the implementation of the different empirically-estimated and growth-based impact functions, by properly accounting for their essetial heterogeneity. Detailed-Process model outcomes were extensively used to calibrate the regionally-differentiated marginal abatement costs curves (MACCs). Furthermore, we customized social welfare formulation to disentangle inter-temporal discount preferences from intra-temporal inequality aversion.
Optimal policies can be evaluated both under a cooperative (social welfare maximization) and non-cooperative (open-loop Nash equilibrium) solving mode. The model is written in GAMS code (publicly released as open-source) and optimized using CONOPT solver.

Main findings

The paper provides a detailed description for all the modelling choices and calibrations applied. In particular, the RICE50+ model achieves four key improvements: 1) it introduces a high level of regional representation, finer than every other benefit-cost optimizing models known in the literature; 2) it provides a direct implementation for recent empirically-estimated impact functions, linking them to local temperature dynamics and preserving their essential heterogeneity; 3) it introduces different coherent socio-economic scenarios calibrated upon DP-IAMs projections; 4) it keeps an adequate trade-off between regional detail and optimization runtime.
Model description is completed with some illustrative results which provide representative examples of benefit-cost outputs. Runs include all socio-economic baselines (SSP1-SSP5), climate-impact specifications and normative preferences. Eventually, a sensitivity analysis (based on the eta-squared correlation ratio) reports an estimated importance of model drivers in determining Global Mean Temperature (GMT) increase in 2100.

Abstract

Benefit-cost Integrated Assessment Models (IAM) have been largely used for optimal policies and mitigation pathways countering climate change. However, the available models are relatively limited in the representation of spatial heterogeneity. This is despite strong evidence of large regional variation of mitigation costs and benefits, institutional capacity, environmental and economic priorities. Here we introduce RICE50+, a benefit-cost optimizing IAM with more than 50 independently deciding regions or countries. Its core foundation is the DICE model, improved with several original contributions. These include new calibrations on actual mitigation cost data, full integration of recent empirically-based impact functions, different socioeconomic reference projections as well as normative preferences, including welfare specifications explicitly featuring inequality aversion. Due to its high level of regional detail, the model can support researchers in better investigating the role of heterogeneity in international cooperation, cross-country inequalities and climate change impacts under a variety of mitigation pathways and scenarios.

1.5 Paper 2 - Persistent inequality in economically optimal scenarios

Research questions

The second contribution focuses on the consequences of the new benefit-cost analyses provided by the formerly-developed RICE50+ model. In particular, it investigates the problem of cross-regional inequality over a wide range of optimal-policy projections.

It addresses the following main research question:

RQ 2. *Which optimal policies are the outcome of the RICE50+ model specifications? Which projections emerge under those scenarios optimizations?*

Related and more-specific sub-questions are also:

RQ 2.1. *Is the Paris Agreement goal an economically optimal target?*

RQ 2.2. *How will efforts, damages, and other main model variables spread across the different countries?*

RQ 2.3. *How do optimal policies compare with current NDCs (Nationally Determined Contributions) 2030-objectives?*

RQ 2.4. *How much is cross-countries inequality (i.e., GDP distribution) affected by climate change and to which extent do optimal policies improve the general outlook?*

Methodology

We adopted the formerly described RICE50+ integrated assessment model to explore a wide range of optimal policies for a large combination of potential scenarios. We run benefit-cost optimizations across all the five socioeconomic (SSPs) baselines, different impact functions, and several normative preferences over time and inequality. The model was executed both in a cooperative (social welfare maximization) and non-cooperative (Nash open-loop equilibrium) solving mode to assess the additional benefit provided by international cooperation. Results projections were extensively analyzed, focusing in particular on regional heterogeneity and inequality aspects.

Main findings

This paper addresses the regional diversity of climate change impacts and mitigation efforts within a unified framework. It shows that climate change exacerbates global inequalities, even if we manage to reduce emissions significantly. Urgent and more ambitious mitigation policies confirm to be strongly necessary to stabilize the temperature increasing, but they alone are not sufficient to close the gap of disparities among regions. Economic progress needs to be both sustainable and inclusive, oriented towards resilient climate adaptation strategies. The results are surprisingly robust across the different socioeconomic scenarios, impact specifications and normative preferences adopted. We confirmed recent literature findings by assessing that the Paris target passes the benefit-cost test. However, as already pointed out by other important contributions, it is achieved only with strong cooperation and immediate action. Last, we appraised how largely insufficient current NDCs policies are, as they mostly align with noncooperative model projections.

Abstract

Benefit-cost analyses of climate policies by integrated assessment models have generated conflicting assessments. Two critical issues affecting social welfare are regional heterogeneity and inequality. These have only partly been accounted for in existing frameworks. In this chapter, we perform benefit-cost analysis using RICE50+, a model with more than 50 regions, calibrated upon emissions and mitigation cost data from detailed-process IAMs, and featuring country-level economic damages. We compare countries' self-interested and cooperative behaviour under a range of assumptions about socioeconomic development, climate impacts, and preferences over time and inequality. Results indicate that without international cooperation, global temperature rises, though less than in commonly-used reference scenarios. Cooperation stabilizes temperature within the Paris goals (1.80°C [1.53°C-2.31°C] in 2100). Nevertheless, economic inequality persists: the ratio between top and bottom income deciles is 117% higher than without climate change impacts, even for economically optimal pathways.

1.6 Paper 3 - An Agent-based negotiating framework for international climate agreements

Research questions

The third contribution of this thesis addresses the problem of modelling international negotiation dynamics. It follows a novel approach based on Agent-Based Modelling. The decision-making structure builds on top of the RICE50+ Integrated Assessment model and its optimal policy projections data.

It is driven by the following main research question:

RQ 3. *How to better model and integrate the distributed decision-making and complex political negotiation dimension in a flexible yet informative framework?*

It articulates into following sub-questions:

RQ 3.1. *How to properly account for the diverse individual multi-objective evaluations and different negotiating strategies?*

RQ 3.2. *Would an Agent-Based framework be a complementary solution to traditional game-theory for modelling international environmental agreements?*

RQ 3.3. *How to better account for time-varying decision forces that drive a repeated COP-like negotiation process?*

Methodology

In this paper we introduce an Agent-Based negotiating framework that aims at reproducing and investigating International Environmental Agreements. It is a simulation model that follows a bottom-up approach, starting from a modelled behaviour for each region-representative negotiator. Few interaction rules, shared as common knowledge, regulate the debate on greenhouse gases emissions regulation and guarantee termination and convergence to an agreement. A mediator supervises and synchronizes the process, although not imposing any minimum participation commitment. Agents generate and update their own emissions mitigation proposals following private multi-objective evaluations over potential upcoming scenarios. In particular, their decision is informed by optimal-policy projections estimated by the coupled RICE50+ Integrated Assessment Model. Additional decision forces can further influence and modify agents' rational positions. These forces help to conceptualize and include different potential risk aversions, impact perceptions or reactions to other players' behaviour over time. The model is coded in Python and will be publicly released soon as open-source.

Main findings

This contribution provides a detailed description for the methodology and all the modelling choices applied. It achieves four key improvements: 1) it introduces a novel approach to support the investigation of the complex problem of International Environmental Agreement negotiation; 2) it provides a primary conceptualization for accounting non-economic payoffs and their influence in a distributed decision-making process; 3) it provides a highly scalable solution that will be easily enriched with additional levels of detail, a higher number of participatory agents, and more sophisticated decision-making techniques which can account for co-benefits fostering individual commitment; 4) it provides a first attempt for calibrating additional decision forcings on the basis of current NDCs proposals and carbon neutrality declarations. Preliminary results show some quantitative participatory consequences for different individual multi-objective evaluations.They favourably suggest that the emerging behaviours of such complex bottom-up modelled dynamics may support the research of the most influential conditions and levers for international cooperation.

Abstract

International Environmental Agreements on greenhouse gases emissions reductions demonstrated to be extremely hard to achieve and uphold. Several studies have been searching for self-enforcing strategies to enlarge cooperation and enforce agreement stability, usually supported by models grounded on game theory. However, the public-good nature of climate change makes it an exceptionally complex problem with many time-varying international issues which are hard to be all accounted for in any game-theoretical framework. Here we propose an agent-based negotiation framework as a novel approach to investigate the complex and distributed decision-making processes of international negotiation on greenhouse gases regulation. The simulation model follows a bottom-up approach, starting from a modelled behaviour for each region-representative negotiator. Agents generate and update their own emissions mitigation proposals following private multi-objective evaluations over potential upcoming scenarios (informed by the RICE50+ Integrated Assessment model regional benefit-cost projections), reactions to other players' proposals, and private negotiating strategies.

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Chapter

2

RICE50+: DICE model at (almost) country level[1]

2.1 Abstract

Benefit-cost Integrated Assessment Models (IAM) have been largely used for optimal policies and mitigation pathways countering climate change. However, the available models are relatively limited in the representation of spatial heterogeneity. This is despite strong evidence of large regional variation of mitigation costs and benefits, institutional capacity, environmental and economic priorities. Here we introduce RICE50+, a benefit-cost optimizing IAM with more than 50 independently deciding regions or countries. Its core foundation is the DICE model, improved with several original contributions. These include new calibrations on actual mitigation cost data, full integration of recent empirically-based impact functions, different socioeconomic reference projections as well as normative preferences, including welfare specifications explicitly featuring inequality aversion. Due to its high level of regional detail, the model can support researchers in better investigating the role of heterogeneity in international cooperation, cross-country inequalities and climate change impacts under a variety of mitigation pathways and scenarios.

2.2 Introduction

As time passes, climate change has become one of the most important and challenging global problems, with potentially severe consequences both for natural ecosystems and for human societies. The Intergovernmental Panel on Climate Change, in his last Special Report (IPCC, 2018), once more calls out the urgent needing for immediate and ambitious mitigating actions. Benefit-cost Integrated Assessment Models (IAM) —connecting climate dynamics with economies and human societies— have been extensively used to estimate optimal mitigation policies balancing impacts, investments, and costs. In this field modelling research has achieved remarkable advancements; however, there remain several improvement directions (Weyant, 2017).

[1]This chapter is drawn from the paper "RICE50+: DICE model at (almost) country level" by P. Gazzotti, submitted to Socio-Environmental Systems Modelling (SESMO) journal and under review at the moment of writing this thesis.

In particular, here we emphasize the key-aspect of spatial heterogeneity representation. Popular benefit-cost optimizing models like RICE (Nordhaus, 2010; Nordhaus and Yang, 1996), PAGE (Hope, 2008), FUND (Anthoff, 2009), C^3IAM(Wei et al., 2020), CWS (Eyckmans and Tulkens, 2003), WITCH (Bosetti et al., 2006), MICA (Lessmann et al., 2015), and STACO (Nagashima et al., 2009), execute from 6 to 16 independent regions at maximum. Despite the coherent grouping criteria applied, this may raise some legitimate doubt on their capability of properly capturing local growth differences, climatic vulnerabilities, and ultimate mitigation costs, as they significantly vary across countries (Berg et al., 2019).

Most notably, recent and debated empirical evidence on climate economic impacts point out strong heterogeneities across countries, with potential winners and losers, robustly related to local temperature deviations (Burke, Hsiang and Miguel, 2015; Dell, Jones and Olken, 2012; Diffenbaugh and Burke, 2019; Kahn et al., 2019). Moreover, they esteem significant higher impacts than previously expected. However, we found only a few attempts of implementing these studies as benefit-cost IAM impact function in the literature. In (Ricke et al., 2018) authors provide country-level impacts projections linked to local temperatures, but do not implement any optimizing framework. Glanemann, Willner and Levermann (2020) implement the esteem by Burke, Hsiang, and Miguel (Burke, Hsiang and Miguel, 2015) —hereafter BHM— in DICE, but, given the single-region nature of this model, they fit an aggregated response to global mean temperature increase. To the best of our knowledge, no direct regional implementation of these empirical impact functions has been included in optimizing IAMs yet.

Besides impacts, abatement cost curves vary remarkably across regions as well, due to specific local aspects (e.g., increasing levels of unemployment rate due to strong decarbonizing policies (Ha-Duong, Grubb and Hourcade, 1997)). Several detailed-process IAMs have extensively estimated marginal abatement cost curves (MACC) projections, but their usage in benefit-costs optimizations is quite circumscribed (Hänsel et al., 2020).

Last, spatial heterogeneity has also a strong repercussion on efforts coordination (e.g., see Li and Rus, 2019; Keohane and Victor, 2016; Nordhaus, 2015). Despite the obvious presence of coalitions, alliances, and shared objectives, any final decision in international cooperation — and real action-taking — is up to each national jurisdiction. This has direct consequences in counterfactual scenarios estimation. In fact, these are usually based on Business-As-Usual (BAU) assumptions, which take into account no mitigation at all. However, recent criticisms point out how these scenarios have implausibly high emissions (Glen, 2016), whereas a more adequate counterfactual reference entails countries reacting to climate impacts on the basis of their pure self-interest.

Here we present a new regional model, called RICE50+, which originates from the well-known Nordhaus' DICE and RICE models and aims at tackling all the aforementioned gaps. This is an optimizing tool that explicitly focuses on cross-region dynamics, with unprecedented local detail for main heterogeneity components. What follows provides a general overview of the model and illustrates all original contributions in its dynamics, data integration and calibration. The description is completed with some illustrative examples showing most-interesting model outputs and sensitivity over benefit-cost drivers importance.

2.3 Model description and calibrations

We built the RICE50+ model pursuing four main objectives: 1) introduce a high level of regional representation, finer than every other benefit-cost optimizing model known in the literature; 2) provide a direct implementation for recent empirically-estimated impact functions, linking them to local temperature dynamics and preserving their essential heterogeneity; 3) introduce alternative and coherent socio-economic scenarios from detailed-process IAM projections; 4) keep an adequate focus on cross-regional implications as well as bearable optimization solving-times, finding a well-balanced compromise with economies detail.

We started from Nordhaus' Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1994; Nordhaus, 2010), among simplest yet most-used and known benefit-cost IAM. Hereafter we always refer to its latest DICE-2016R2 formulation, used in Nordhaus, 2018, unless otherwise stated. The model is written in GAMS and is executed using CONOPT, a solver for large-scale nonlinear optimization (NLP). What follows will provide a detailed description for all implemented advancements, original contributions, and new calibrations operated.

Time and regions

The model runs on discrete time-steps, lasting five years each, starting from 2015. To avoid the end-of-world biasing effect (i.e., a last total-consumption period without any investment or mitigation policy), run horizon goes up to the year 2300. Meaningful projections outcomes are then extracted from the 2015-2100 interval only.

Figure 2.1 shows all independently-deciding regions provided. They have been chosen according to the finest detail available from local abatement costs data. Note that European Union is fragmented into single country-states (but we included also the possibility to group them together, acting as a single player), whereas widest regions are those aggregating countries of Persian Gulf (Gulf), former Soviet-Union members (FSU), middle-East group (MEast), secondary players from South-East-Asia (RSEAs), Latin-America (RSAm), and Subsaharan Africa (SSAfr). This last one, notably, turns up as the widest geographical and political aggregation left. Unfortunately, it reflects lack of detailed data and high uncertainties currently concerning several African regions. We plan to further subdivide it in future model updates as soon as more detailed data will become available. See Table 2.A in Appendix 2.A for a full mapping between model regions and belonging ISO3 countries.

Economy and projections

RICE50+ regional economies largely inherits from Nordhaus' DICE/RICE models representation. GDP outputs are expressed in Purchasing Power Parity (PPP), and therefore they adjust for price differences across countries, providing a correct comparison of income levels across countries. GDP gross output for region i at each timestep $Y_{\mathrm{GROSS},i}(t)$ is the result of a Cobb-Douglas production

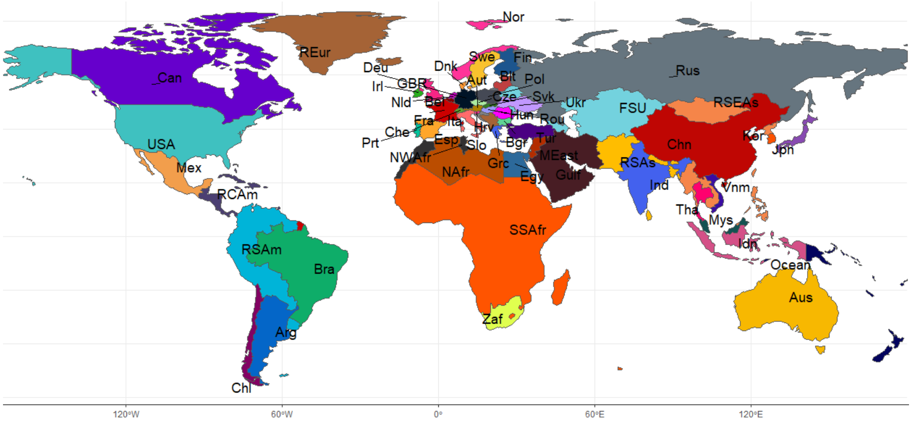

Figure 2.1: Geographical representation for model regions. Subdivision reflects the finest available resolution for local abatement cost curves.

function in capital $K_i(t)$, labour $L_i(t)$ and total factor productivity $\text{TFP}_i(t)$:

$$Y_{\text{GROSS},i}(t) = \text{TFP}_i(t) \cdot K_i(t)^{\alpha} \cdot L_i(t)^{1-\alpha}. \tag{2.1}$$

Labour and TFP have exogenous trends that have been calibrated to match the Shared Socio-economic Pathways (SSP) (O'Neill et al., 2014; Riahi et al., 2017) population and GDP-growth data projections. Hence, the model can be executed over five alternative and coherent future reference-baselines, from SSP1 to SSP5. To expand SSPs projections beyond 2100 (country-level data cover 2015-2100 period only), we followed a conservative approach. We extrapolated the growth-rates from last available time-period for both population and GDP, and we progressively reduced them up to 2200. From 2200 on, levels stabilize and keep constant till the end of model time-horizon. This approach was chosen to avoid potentially unjustified long-term conjectures and, at the same time, reduce model biasing at minimum for current century. Figure 2.6 in Appendix 2.C shows stacked projections for both regional population and GDP in SSP2 scenario.

In optimizing models the savings-rate $S_i(t)$ are usually left as free variables to be evaluated by the solver. They determine investments and consequent capital formation according to equation:

$$I_i(t) = S_i(t) \cdot Y_i(t), \tag{2.2}$$

and:

$$K_i(t+1) = (1 - d_k)^{\Delta t} \cdot K_i(t) + \Delta t \cdot I_i(t), \tag{2.3}$$

where variable $Y_i(t)$ represents the final GDP after subtracting abatement costs $\Lambda_i(t, \mu_i)$ to GDP net-of-damages $Y_{\text{NET},i}(t)$:

$$Y_i(t) = Y_{\text{NET},i}(t) - \Lambda_i(t, \mu_i). \tag{2.4}$$

In RICE50+ we implemented two alternative execution modes: 1. *free-option*, where $S_i(t)$ variables are left endogenous and freely optimized as in the original DICE/RICE definition; 2. *fixed-option*, where $S_i(t)$ variables are fixed, starting from current values (WEO) and linearly converging to DICE-2016R2 optimal projection $\overline{S}$ by the end of the time-horizon. This optimal level is evaluated as a consequence of economic assumptions for: capital elasticity in production function α, depreciation rate on capital per year d_k, elasticity over marginal utility of consumption η, elasticity of output with respect to capital δ, and pure rate of social time preference ρ (also known as utility discount rate):

$$\overline{S} = \alpha \cdot \frac{(d_k + \delta)}{(d_k + \delta \cdot \eta + \rho)}. \tag{2.5}$$

Emissions and carbon-intensity calibration

Industrial emissions are directly related to output $Y_{\mathrm{GROSS},i}(t)$ and mitigation choice $\mu_i(t)$ by the exogenous carbon-intensity $\sigma_i(t)$, which exemplifies fossil-fuel-share in production sectors:

$$E_{\mathrm{IND},i}(t) = \sigma_i(t) \cdot Y_{\mathrm{GROSS},i}(t) \cdot (1 - \mu_i(t)) \,. \tag{2.6}$$

It varies according to SSP-reference projection and encompasses specific assumptions over carbon-saving technological change (e.g., see Nordhaus, 2008). We calibrated $\sigma_i(t)$ following a two-steps process: first, we estimated values for SSP2 baseline (our default middle-of-the-road reference), then we proportionately determined other-SSPs values accordingly. We started from DICE carbon-intensity definition, applied to each region:

$$\sigma_i(t+1) = \sigma_i(t) \cdot \exp\big(g_i(t) \cdot \Delta t\big), \tag{2.7}$$

where the cumulative improvement of energy efficiency $g_i(t)$ evolves according to:

$$g_i(t+1) = g_i(t) \cdot (1 + d_i)^{\Delta t}. \tag{2.8}$$

For all curves, we imposed their passage through known 2015 levels. Then, we estimated optimal decreasing rates $\overline{d_i}$ — and consequently $\overline{g_i}(t)$ and $\overline{\sigma_i}(t)$ terms — which minimize the difference between resulting emissions (obtained by eq.(2.6), imposing $\mu_i(t) = 0$), EnerData MACC baselines (available for 2025-2040 period, as described later in dedicated section), and regional projections from SSP2-marker-model (Message-GLOBIOM, available for 2015-2100 period). Beyond 2100 we opted for a conservative smooth convergence, for each region, to DICE-2016R2 global carbon-intensity levels by year 2200. Therefore, at each point in time, final carbon-intensity results as a convex-combination of two components:

$$\sigma_{\mathrm{ssp2},i}(t) = \big(1 - \mathrm{cc}(t)\big) \cdot \overline{\sigma_i}(t) + \mathrm{cc}(t) \cdot \sigma_{\mathrm{DICE}}(t), \tag{2.9}$$

with coefficient $\mathrm{cc}(t)$ following a smooth sigmoid transition from 0 to 1 for $t \in [2100, 2200]$.

As second step, we evaluated carbon-intensities also for other socio-economic scenarios. We added $m_i(ssp)$, an SSP-dependent multiplier, in eq.(2.7), including also previously-optimized $\overline{g_i}(t)$ term:

$$\sigma_i(ssp, t+1) = m_i(ssp) \cdot \sigma_i(ssp, t) \cdot \exp\big(\overline{g_i}(t) \cdot \Delta t\big). \tag{2.10}$$

As before, we imposed passage through 2015 levels and computed optimal $\hat{m}(ssp)$ — and $\hat{\sigma_i}(ssp, t)$ — values that minimize differences between resulting emissions and regional projections from each SSP-marker-model. Beyond 2100 we kept the convex combination between calibrated curves and an SSP-corrected DICE global carbon-intensity:

$$\sigma_i(ssp,t) = \big(1 - \mathrm{cc}(t)\big) \cdot \hat{\sigma_i}(ssp,t) + \mathrm{cc}(t) \cdot \xi(ssp) \cdot \sigma_{\mathrm{DICE}}(t). \tag{2.11}$$

Correction factor:

$$\xi(ssp) = \frac{\hat{\sigma}_{\mathrm{World},2100}(ssp)}{\overline{\sigma}_{\mathrm{World,ssp2},2100}} \tag{2.12}$$

reflects the resulting proportion, in year 2100, between each SSP world-aggregated carbon-intensity (from calibrated values) and SSP2 one. Figure 2.7 in Appendix 2.C reports some examples for these qualitative evaluations.

Regions can reduce their baseline emissions by increasing their choice over percentage mitigation $\mu_i(t) \in [0\%, 120\%]$. Unlike original DICE/RICE, we introduced limitations in the maximum mitigation increasing rate. Following assumptions as in Hänsel et al. (2020), we fixed a 20% maximum increase every (5-years) period. As a direct consequence, negative emissions (ranging from 100% to 120% mitigation as in original DICE) cannot be achieved before the year 2050 by construction. The same limit is applied to decreasing mitigation rates, preventing the possibility of abrupt reverting emissions to BAU levels.

Abatement costs and MAC curves

To determine regional Marginal Abatement Cost (MAC) curves we differentiated between three time periods. For the near future (2025-2040), we fitted curves on EnerData-EnerFuture projections, from the detailed process-based model POLES (Després et al., 2018), an energy-sector model jointly developed with the European Commission. For the rest of the century, we extracted emissions and abatement potential from detailed-process IAMs reviewed in the IPCC SR1.5 (IPCC, 2018). In the very long term (post 2100), model assumptions converge to DICE-backstop trends.

Data-driven phase

To evaluate the different abatement costs, we started from EnerData-EnerFuture MAC curves, which provide, for each region, industrial CO2 reductions for several carbon-price levels over 2025-2040 time period. First, we identified the best continuous curve fitting those data. We compared R-squared goodness measures and qualitatively analyze performances for biggest economies to this end (see Figure 2.8 in Appendix 2.C for a representative example). A fourth-exponent polynomial curve turned out being the best-matching model:

$$C_{\mathrm{PRICE},i}(t,\mu) = a_i(t)\mu_i + b_i(t)\mu_i^4. \tag{2.13}$$

We extended region-specific $a_i(t)$ and $b_i(t)$ coefficients also to time-steps not directly covered by EnerData projections to preserve a primal differentiating component. Then, we introduced an additional multiplying correction-factor $\nu_i(t)$ to better regulate these curves to the state-of-the-art assumptions in the Integrated Assessment Modelling community:

$$\mathrm{MAC}_i(t,\mu) = \nu_i(t) \cdot \Bigg(a_i(t)\mu_i + b_i(t)\mu_i^4\Bigg). \tag{2.14}$$

Hence, we extracted several MAC curves from SSPs database, using policy scenarios with carbon-price projections. We used those curves to evaluate the best value $\overline{\nu}(t)$, equal for each region, which minimizes the difference between RICE50+ global abated emissions and the SSP ensemble's median levels.

Backstop phase

For the long-term period, give the absence of any regional-detailed projection, we decided once more to follow original DICE model specification implementing a global backstop-technology curve. It is defined as:

$$\mathrm{BT}(t) = pback \cdot (1 - gback)^{t-1}, \tag{2.15}$$

with $pback = 550$ and $gback = 0.025$ as in DICE2016-R2.

After an intermediate transition phase (described in next section), from time $t \geq t_{\mathrm{BT}}$ we imposed matching backstop values for a 100% mitigation level ($\hat{\mu_i} = 1$) on each regional MAC curve, obtaining correction factor $\hat{\nu_i}(t)$ values accordingly:

$$\hat{\nu_i}(t) \cdot \Big(a_i(t)\hat{\mu_i} + b_i(t)\hat{\mu_i}^4\Big) = \mathrm{BT}(t)\Big|_{t \geq t_{\mathrm{BT}}}. \tag{2.16}$$

Transition phase

Transition towards common backstop begins in 2045 (first time without EnerData projections) and terminates in t_{BT}. It is regulated by the correction parameter $\nu_i(t)$ which moves from $\overline{\nu}(t)$ (for $\bar{t} = 2040$) to $\hat{\nu_i}(t)$ (for $t = t_{\mathrm{BT}}$) according to:

$$\nu_i(t) = \hat{\nu_i}(t) - \mathrm{cb}(t) \cdot \max\Big(\hat{\nu_i}(t) - \overline{\nu_i}(t), 0\Big). \tag{2.17}$$

Transition coefficient $\mathrm{cb}(t)$ follows a smooth sigmoid dynamic:

$$\mathrm{cb}(t) = \frac{1}{1 + e^{-k \cdot \left(t - \frac{1}{2}\left(t_{\mathrm{BT}} - \bar{t}\right)\right)}}, \tag{2.18}$$

where parameter k affects general transition speed and smoothness. We qualitatively selected k and t_{BT} after evaluating several tests and comparing model responses to increasing carbon-tax policies with SSPs models ensemble. Figure 2.9 in Appendix 2.C shows an example for this qualitative evaluation.

Final abatement costs

Regional abatement costs Λ_i are related to mitigation level μ_i according to the equation:

$$\Lambda_i(t, \mu_i) = \int_0^{\mu_i} E_{\mathrm{BAU},i}(t) \cdot \mathrm{MAC}_i(t, \mu_i)\, d\mu, \tag{2.19}$$

where $E_{\mathrm{BAU},i}(t)$ represents regions' baseline industrial emissions, as from eq.(2.6) without mitigation ($\mu_i(t) = 0$). Therefore, from eq.(2.14), it follows that in RICE50+ final abatement costs are evaluated as:

$$\Lambda_i(t, \mu_i) = \nu_i(t) \cdot E_{\mathrm{BAU},i}(t) \cdot \left(\frac{a_i(t)}{2}\mu_i^2 + \frac{b_i(t)}{5}\mu_i^5\right). \tag{2.20}$$

Global and local climate

The atmospheric concentrations of greenhouse gases are obtained with the usual three-box carbon sink model. CO_2-effect on radiative forcing $\mathrm{RF}_{\mathrm{CO_2}}(t)$ is determined by its changes in concentration $M_{\mathrm{CO_2}}(t)$ from pre-industrial level $M_{\mathrm{CO_2,pre}}$ as:

$$RF_{\mathrm{CO_2}}(t) = \mathrm{a_m} \cdot \Bigg(\ln\left(M_{\mathrm{CO_2}}(t)\right) - \ln\left(M_{\mathrm{CO_2,pre}}\right)\Bigg) \tag{2.21}$$

with coefficient $\mathrm{a_m} = 5.35$. Then, total forcing results from equation:

$$RF(t) = RF_{\mathrm{CO_2}}(t) + RF_{\mathrm{OGHG}}(t), \tag{2.22}$$

where $RF_{\mathrm{OGHG}}(t)$ is an exogenous addition related to other-greenhouse-gases (OGHG) contribution (described later on). Finally, the global atmospheric mean temperature increase ΔGMT(t) is computed following the DICE-2016R2 two-layer model, adjusted in its exchange-coefficients to match the MAGICC6 model emulation (Meinshausen, Raper and Wigley, 2011).

In most climate-economy IAMs, climate variables are considered only at the global level due to computational reasons. For our purpose, however, regional temperature responses to greenhouse gas emissions are also needed, to accurately consider the spatial heterogeneous warming response. Therefore, we used the CMIP5 database (Taylor, Stouffer and Meehl, 2011) to implement and calibrate a statistical downscaling method. Data provide historical projections for both temperature and precipitation at the 0.5° gridded level on an averaged annual basis. Values were aggregated to the country level using population weights, obtaining observations for $N = 244$ countries and territories. Then, from different representative concentration pathways (RCPs), implemented by several global climate models, we considered the mean of model ensemble to link the global-mean-temperature increase (ΔGMT) to the country-level average annual temperature. This procedure was repeated for all the RCPs. Finally, we run a linear regression on this dataset to estimate the ultimate effect of global temperature increase $\Delta\mathrm{GMT}(t)$ on local temperature levels in countries n at time t (measured in absolute °C):

$$T_n(t) = \mathrm{p}_n + \mathrm{q}_n \Delta\mathrm{GMT}(t) \tag{2.23}$$

The R^2 goodness measure for the estimated regressions varies between 0.95 and 0.999. Due to the linear relationship, model 57-regions equivalent p_i and q_i coefficients — which determine regional temperatures $T_i(t)$ — are the population-weighted average of the associated n countries values.

Climate impact functions

The traditional approach, used in most IAMs, consists in calibrating a region specific damaging curve, typically based on global temperature increase. Projected impacts from climate change often include factors like sea-level rise, increased energy demand, and agricultural productivity changes. Moreover, non-market damages including ecosystem losses, non-market health impacts, and catastrophic events are also often taken into account. Regional impacts are thus computed using a damage function which depends on global mean temperature GMT(t) as:

$$\Omega_i\big(T(t)\big) = a_{1i} \cdot \Delta\mathrm{GMT}(t) + a_{2i} \cdot \Delta\mathrm{GMT}(t)^{a_{3i}}, \tag{2.24}$$

where a_{1i}, a_{2i}, a_{3i} are calibrated region-specific coefficients. The impact factor is then applied as GDP discount (or consumption discount, depending on the model):

$$Y_{\mathrm{NET},i}(t) = \frac{Y_{\mathrm{GROSS},i}(t)}{\Omega_i(t)}. \tag{2.25}$$

This approach has some drawbacks. Most notably, it is calibrated upon points and usually at low degrees of warming. Therefore, the extrapolation can hardly be justified as well-based on empirical evidence. Moreover, affecting solely the *level* of GDP (or consumption), it has been criticized as underestimating the full impacts for the long-run growth potential of the economy (Pindyck, 2013).

In RICE50+ we introduced an alternative approach, based on recent empirically-estimated impact functions linked to the regional temperature patterns. We implemented different specifications of linear impacts $\delta_{i,\mathrm{spec}}(t)$ on the GDP per-capita baseline growth rate $\mathrm{g}_i(t)$. Hence growth between period t and $t+1$ can be written as:

$$\mathrm{GDP}_{\mathrm{CAP},i}(t+1) = \mathrm{GDP}_{\mathrm{CAP},i}(t)\big(1 + \mathrm{g}_i(t) + \delta_{i,\mathrm{spec}}(t)\big). \tag{2.26}$$

Replacing in the definition of $\mathrm{GDP}_{\mathrm{CAP},i}(t) = \frac{Y_{\mathrm{NET},i}(t)}{L_i(t)}$ the traditional DICE impact definition of eq.(2.25), and then equations (2.1), (2.2), (2.3), we obtained a new recursive formula for impacts $\Omega_i(t)$:

$$\Omega_i(t+1) = \frac{\mathrm{TFP}_i(t+1)}{\mathrm{TFP}_i(t)} \left(\frac{L_i(t+1)}{L_i(t)}\right)^{-\alpha} \cdot \Upsilon_i\big(t\big)^{\alpha} \cdot \frac{1 + \Omega_i(t)}{\big(1 + \mathrm{g}_i(t) + \delta_{i,\mathrm{spec}}(t)\big)^{\Delta t}} - 1, \tag{2.27}$$

where:

$$\Upsilon_i\big(t\big) = (1 + \delta_k)^{\Delta t} + \Delta t \cdot S_i(t) \cdot \mathrm{TFP}_i(t) \cdot \left(\frac{L_i(t)}{K_i(t)}\right)^{1-\alpha} \cdot \frac{1}{1 + \Omega_i(t)}.$$

This implementation is perfectly consistent with the growth-rate empirical impact estimation of eq.(2.26). However, it can lead to numerical issues, notably with endogenous savings rate. Therefore, we also implemented an alternative approximate rule $\tilde{\Omega}_i(t)$, equivalent to the standard $\Omega_i(t)$ in DICE:

$$\tilde{\Omega}_i(t+1) = (1 + \tilde{\Omega}_{it}) \frac{1}{\big(1 + \delta_{i,\mathrm{spec}}(t)\big)^{\Delta t}} - 1. \tag{2.28}$$

A tentative proof for this equation is provided in Appendix 2.B. Eq.(2.27) is therefore preferred when *fixed-option* is enabled for savings rate; eq.(2.28) otherwise.

Burke et al. (2015) specification

The regional temperature patterns allowed us to integrate an impact function based on Burke, Hsiang and Miguel (2015), who found an inverse U-shaped relationship between economic growth and average annual temperatures across countries and over time. Grounded on fifty years of data across a large set of countries, their finding is surprisingly robust and thus able to provide a well-calibrated alternative.

The authors estimate a quadratic relationship for both temperature and precipitation (we concentrated on the former, as it is easier to work with and has less uncertainty). Using long-run estimates and a single equation for all countries, they obtain, as base-case, a function of growth effects solely related to country-level temperature $T_i(t)$:

$$\mathrm{h}\big(T_i(t)\big) = 0.0127 \cdot T_i(t) - 0.0005 \cdot T_i(t)^2. \tag{2.29}$$

Impacts on the production growth rate $\delta_{i,\mathrm{BHM}}(t)$ are then obtained by computing the difference between the result of eq.(2.29) at time t and its value under *reference* temperatures T_{i0} (defined as the average values between 1980 and 2010):

$$\delta_{i,\mathrm{BHM}}(t) = \mathrm{h}\big(T_i(t)\big) - \mathrm{h}\big(T_{i0}\big). \tag{2.30}$$

We considered four major alternative specifications for the BHM eq.(2.29) impact function coefficients. These include different time lags —capturing short-run (SR) and long-run (LR) impacts— and the extent to which rich and poor countries' income differentiation is accounted for. They also implicitly allow for different historical adaptation to longer-run climate. Specifications coefficients are reported in Table 2.1.

Spec.	T_i coeff.	T_i^2 coeff.	Applies for
SR	0.01271	-0.00048	all
LR	-0.00374	-0.00009	all
SRdiff	0.00889	-0.00031	rich
SRdiff	0.02543	-0.00077	poor
LRdiff	-0.00269	-0.00002	rich
LRdiff	-0.01860	0.00015	poor

Table 2.1: Specifications coefficients for BHM impacts.

Dell, Jones and Olken (2012) specification

Another contribution by Dell, Jones and Olken (2012) provides a different and forerunner empirical estimation for local impacts. Authors estimate a linear relationship between local temperature and economic growth. Impacts $\delta_{i,\mathrm{DJO}}(t)$ on the production growth rate are obtained on the basis of a general effect (almost irrelevant), and a more significant negative effect of about additional 1.655 percentage point reductions for poor countries only (i.e., having GDP per-capita [PPP] below the median in the base year):

$$\begin{aligned}\delta_{i,\mathrm{DJO}}(t) =& 0.00261 \cdot \Big(T_i(t) - T_{i0}\Big) \\ & -0.01655 \cdot \Big(T_i(t) - T_{i0}\Big)\Big|_{\mathrm{GDPpc}_i(t_0)<\mathrm{Median}(\mathrm{GDPpc}_i(t_0))}\end{aligned} \tag{2.31}$$

Its implementation in RICE50+ model follows what already described in the previous section.

Kahn et al. (2019) specification

A third empirical-based contribution by Kahn et al. (2019) similarly estimates a linear relationship, related to deviations of the country-level temperatures over the historical norm. Their main results point out that a temperature increase by one degree is associated with a growth rate reduction by 5.86 percentage points, while a decrease by one degree implies a reduction by 5.20 percentage points. The authors do not find a significant differentiated response between rich and poor countries. We used their main specification which accounts a 30 years interval for computing the historical norm as moving average (in our case starting from 1980-2010, consistent with the case of Burke, Hsiang and Miguel (2015)). We obtained the following specification for the growth effect $\delta_{i,\mathrm{Kahn}}(t)$:

$$\begin{aligned}\delta_{i,\mathrm{Kahn}}(t) =& -0.0586\Big(\big[T_i(t) - \overline{T}_i(t-1)\big] - \big[T_i(t-1) - \overline{T}_i(t-2)\big] \Big)\Big|_{T_i(t)>\overline{T}_i(t-1)} \\ & -0.0520\Big(\big[T_i(t) - \overline{T}_i(t-1)\big] - \big[T_i(t-1) - \overline{T}_i(t-2)\big] \Big)\Big|_{T_i(t)<\overline{T}_i(t-1)}\end{aligned} \tag{2.32}$$

with $\overline{T}_i(t-1) = n^{-1}\sum_{\tau=1}^{n} T_i(t-\tau)$ for $n = 6$ (each t accounts for 5 years).

Long-run impacts bounding

Cumulative growth impacts resulting from aforementioned functions can lead, for some countries, to steep and extreme values (both positive and negative) along the three-centuries solving period. To dampen this degenerating trend and minimize the risk of biasing model optimal decisions, we decided to impose a maximum bound to local impacts. After some testing, we opted for the best-compromise of limiting GDP impacts within $[+100\%, -100\%)$ interval over no-climate-change baseline.

Cooperation and social welfare

Regions maximize their inter-temporal welfare in either a non-cooperative (self-interested) or cooperative setting. The former yields the Nash equilibrium by optimizing each one's mitigation strategy, taking the others' behavior as given. This is implemented through an iterative algorithm that converges to the open-loop Nash equilibrium. On the other hand, the cooperative setting implies a global social planner which maximizes an utility function aggregating the welfare of all regions.

As in the original DICE/RICE models, it optimizes the flow of generalized consumption over time. This is modelled assuming that regions maximize the following social welfare function:

$$W = \sum_n \sum_t \left[w(t,n) \cdot L(t,n) \cdot \left(\frac{1}{1-\eta} \cdot \left(\left(\frac{C(t,n)}{L(t,n)} \right)^{1-\eta} - 1 \right) - 1 \right) \cdot (1+\rho)^{-t} \right]. \tag{2.33}$$

Parameter ρ denotes the pure rate of social time preference, while η is the inter-temporal elasticity of substitution.

RICE model uses Negishi weights for $w(t,n)$, but their distortion of inter-temporal preferences has been criticized and their welfare economic implications are at odds with welfare economics (e.g., see Stanton, 2010). In RICE50+ we implemented a welfare function based on disentangled Epstein-Zin preferences over inter-temporal discount ρ (as in original formulation) and regional inequality aversion γ:

$$W = \sum_{t=1}^{T} \left[\frac{1}{1-\eta} \left(\sum_n w_{\text{pop}}(t,n) \left(\frac{C(t,n)}{L(t,n)} \right)^{1-\gamma} \right)^{\frac{1-\eta}{1-\gamma}} - 1 \right] \cdot (1+\rho)^{-t}, \tag{2.34}$$

with population-weights $w_{\text{pop}}(t,n) = L(t,n) / \left(\sum_n L(t,n)\right)$ and $\gamma \neq 1$ condition. Parameter ρ is set to 1.5% in our default specification, and $\eta = 1.45$ is close to what expert elicitation by Drupp et al. (2018) has found. For $\gamma = 0$, the resulting objective simply maximizes world average consumption while for $\gamma = \eta$, the formulation collapses to the standard DICE welfare function. Increasing γ value allows a gradual change from equal marginal utility to population weighting. Atkinson and Brandolini, 2010 consider γ values between 0.2 and 2.5 as defensible (see also Berger and Emmerling, 2017; Emmerling et al., 2016). For our default specification we chose an intermediate value of $\gamma = 0.5$, close to the value found in (Tol, 2010) or values used in (U.S. Census Bureau, 2000). Table 2.2 show four main reference levels for γ, tested in the model.

Parameter γ value	Interpretation
0	No inequality aversion
0.5	Intermediate inequality aversion ($\gamma < \eta$)
1.45	High inequality aversion, ($\gamma = \eta$)
2	Very high inequality aversion, ($\gamma > \eta$)

Table 2.2: Inequality alternative scenarios run.

Other GHG and land-use effect

Land-use (LU) and other greenhouse gases (OGHG) are not the main focus for this model. Therefore, we decided to keep them as a simple exogenous addition (like in original formulation), providing some minor improvements.

OGHGs contribute to an additional forcing RF_{OGHG} which, summed to CO2-related RF_{CO_2}, generates final climate forcing (see eq. 2.22). We extracted data from SSPs models (baseline and policy experiments) for both forcing components. We found that they can be linked, with an acceptable approximation ($R^2 = 0.608$), by a linear model. In RICE50+ additional OGHG contribution is thus directly estimated from CO2 forcing by the linear regression:

$$RF_{\mathrm{OGHG}}(t) = r \cdot RF_{\mathrm{CO_2}}(t) + s, \tag{2.35}$$

with $r = 0.199$ and $s = -0.011$.

To calibrate regional land-use, we aggregated starting country-levels $E_{\mathrm{LU},i}(t_0)$ from the country-level PRIMAP historical database (Gütschow et al., 2016). We took the mean values between 2010 and 2015 to reduce the impact of historical fluctuations (quite common in LU emissions). We kept DICE original decreasing trend, now applied to each region:

$$E_{\mathrm{LU},i}(t) = E_{\mathrm{LU},i}(t_0) \cdot (1-d)^{t-1} \tag{2.36}$$

and we differentiated between two alternative scenarios. In the first case all countries are affected by the decreasing trend. Therefore, high-emitting countries lower their emissions over time, while already negative-emitting countries increase their contributions towards the common zero-value asymptote. Related cumulative LU-emissions result almost perfectly-matching global DICE2016-R2 equivalent. This scenario is enabled for non-mitigative baseline experiments. In the second case we applied discounting dynamics only to those countries which have positive starting values, while keeping constant already-negative ones. This leads to a more ambitious cumulative projection, which is therefore used when performing benefit-cost optimizations.

2.4 Illustrative results

We support model description with some illustrative results which provide representative examples of benefit-cost outputs. Runs include all socio-economic baselines (SSP1-SSP5) and climate-impact specifications. We included all four representative levels for inequality aversion (γ) from Table 2.2, covering the full range suggested by Atkinson and Brandolini (2010). We also run three alternative values for the utility discount rate ρ over the 0.1% - 3% interval. Both cooperation and non-cooperation solving modes are presented.

Figure 2.2 shows main global-aggregated outcomes. Panel (a) shows optimal projections for world emissions trajectories, where color depicts cooperation under increasing inequality aversion. Thicker lines highlight projections for a representative intermediate SSP2 reference, with BHM-SR impacts and 1.5% utility discount rate. Non-cooperative outputs present significantly lower emissions than no-climate-change Business-As-Usual (BAU). They also visibly exhibit the widest range, suggesting a strong correlation with scenario definition. On the contrary, under cooperation, only inequality neutrality ($\gamma = 0$) presents a noticeable variation. From $\gamma = 0.5$ to higher values, all projections converge to a circumscribed, highly-mitigative range, with negative emissions reached in the second half of the century. On panel (b), associated optimal Global Mean Temperature (GMT) increase distributions are reported. They consistently follow described emissions trajectories, reflecting both ranges and ultimate target ambition.

The effect of inequality aversion in the model is well illustrated by Figure 2.3, panel (a). Here mitigative efforts from all scenarios (reported as reduction

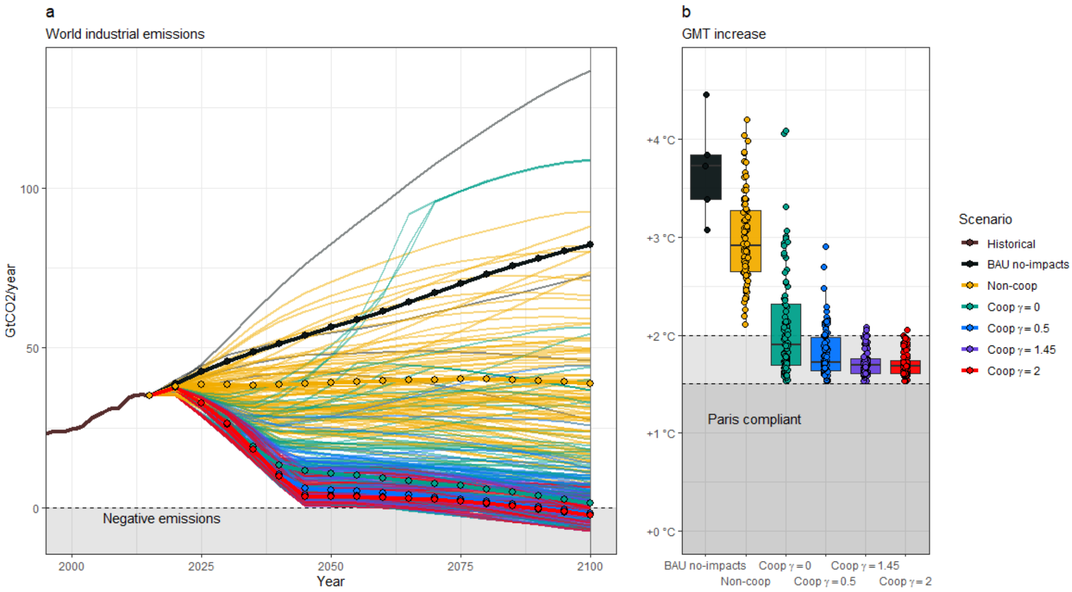

Figure 2.2: Optimal world-aggregated emissions projections (a) and 2100 Global Mean Temperature (GMT) increase distribution (b). Colors distinguish among progressively increasing cooperation and inequality aversion. Results include all impact specifications, discount rates, and SSPs baselines.Thicker lines highlight projections for a representative intermediate SSP2 reference, with BHM-SR impacts and 1.5% utility discount rate.

percentages of baseline emissions) are associated with regions GDP per-capita, for year 2050. Point dimensions account for regions population, while colors indicate non-cooperation or cooperation with increasing inequality aversion. As evidenced by population-weighted linear regressions, the higher the cooperation and inequality-concerning, the less the burden left to poorest high-populated states (those facing also strongest climate impacts). However, while on one side we see inequality aversion triggering a true concerning from richest regions, we notice also a saturating effect, since values higher than 1.45 do not vary substantially the result anymore. The marked effects of cooperation are also visible at finer scale in Figures 2.3b and 2.3c. Here, local population-weighted temperature-increase projections are reported for year 2100, showing a significant reduction under cooperation.

Figure 2.4 depicts residual damages distribution in 2100, under SSP2 baseline and non-cooperative scenario. Under BHM specifications, short-run impacts (SR) generate winners (cold countries) and losers (warm countries), while long-run impacts (LR) negatively affect all countries. Differentiated rich/poor responses exacerbate both the scenarios. DJO also depicts a marked difference between the two groups, while Kahn specification projects negative-only impact as all countries deviate from their historical norm.

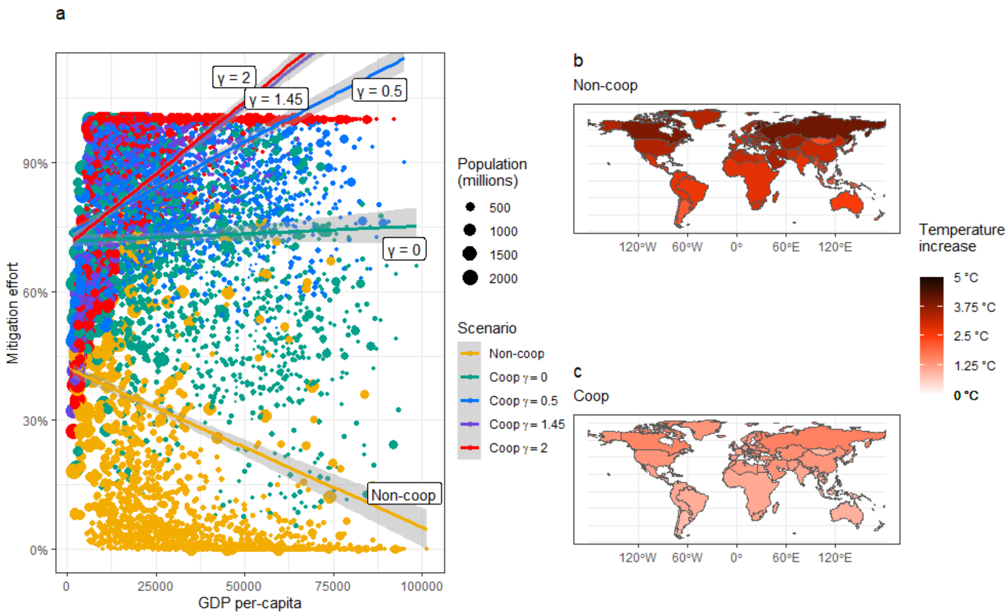

Figure 2.3: Panel (a) reports 2050 regions mitigation efforts over their GDP per-capita for all scenarios tested. Colors and population-weighted regression lines show the ultimate effect of cooperation and inequality aversion in the model. Panel (b) and (c) show local population-weighted average temperature increase in 2100 under non-cooperation and cooperation cases. Baseline scenario is SSP2 with intermediate values for utility discount rate and inequality aversion.

Last, in Figure 2.5 a sensitivity heatmap reports the estimated importance of model drivers in determining GMT increase in 2100. For each of three major projected categories (i.e., heatmap rows: Overall, Coop-only, Non-coop-only) the eta-squared correlation ratio (evaluated from an ANOVA of GMT outputs) denotes a percentage measure of each driver importance. Based on the law of total variance, the correlation ratio does not require the variables to be independent or identically distributed. First-row values (*Overall*, accounting both for cooperative and non-cooperative outputs) confirm that, unsurprisingly, cooperation is by-far the most determining driver. More interestingly, we observe that *Non-coop* scenarios (third row) are largely driven by socio-economic baselines, followed by impacts definition and the utility discount rate. In contrast, *Coop* scenarios (second row) are proportionally driven more by the normative utility discount rate and inequality aversion than impacts or SSP projections.

2.5 Conclusions

In this paper we presented RICE50+, an extension of Nordhaus' RICE/DICE Integrated Assessment Models, featuring the noteworthy granularity of 57 independently-deciding regions. We extensively described all the introduced

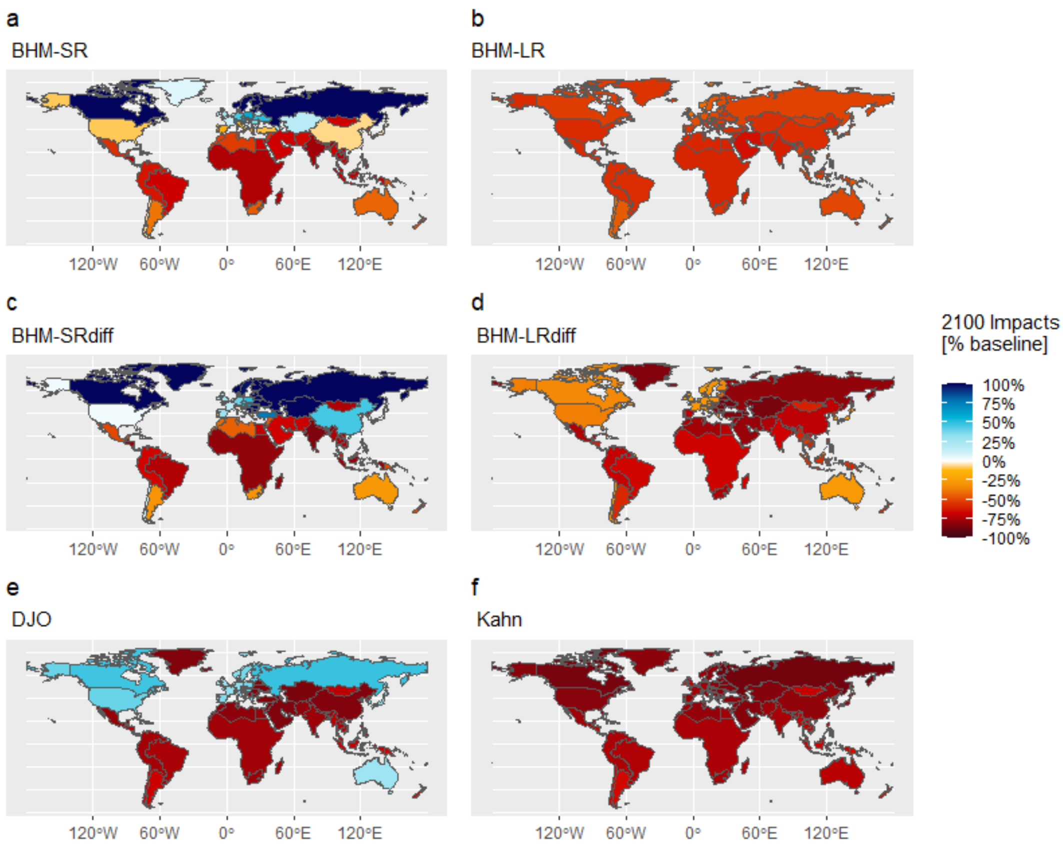

Figure 2.4: Impacts distribution in 2100 for each implemented specification under SSP2 baseline and intermediate utility discount rate. Only non-cooperative (most extreme) scenarios are reported.

novelties: the calibrations of local economic projections, mitigation costs, climate and temperatures downscaling; the direct implementation of impact functions based on recent empirical findings; last, the alternative solving options for cooperation and inequality aversion. It is worth pointing out also that we implicitly demonstrated the solving feasibility for optimizations under such a disaggregated detail level. In fact, IAM complexity may rapidly escalate, turning fast to unbearable solving times. Some illustrative experiments confirmed that regional detail makes a significant difference in benefit-cost outputs. Moreover, we noticed also that, under cooperation, the degree of inequality aversion has a strong impact both on the global pathway and regional distribution of mitigation efforts.

Several future developments and improvements have already been identified at this stage. They include the implementation of time-varying coalitions, the introduction of adaptation dynamics (currently missing), a better representation of endogenous spillovers from technological changes, and estimation of potential consequences from geoengineering action. The automatized process which performs all described calibrations can be reused and readjusted to any future

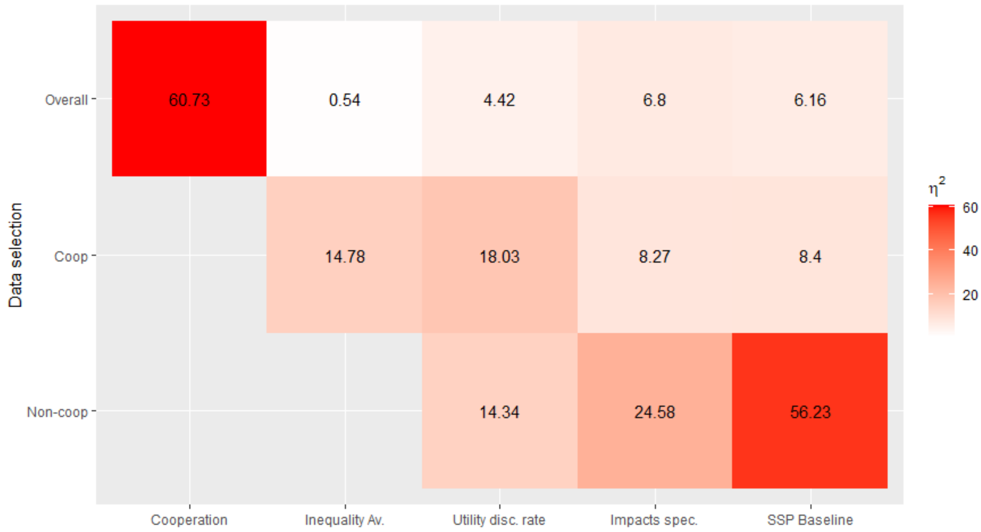

Figure 2.5: Uncertainty drivers associated with global mean temperature (GMT) increase projected in 2100. For each of three major categories (Overall, Coop. only, Non-coop. only) the correlation ratio (η^2) expresses a percentage measure of drivers importance to the final outcome.

data-source update or findings.

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2.A Model regions and countries mapping

Regions List		
Region	Description	Countries ISO3 numeric Code
Arg	Argentina	ARG
Aus	Australia	AUS
Aut	Austria	AUT
Bel	Belgium	BEL
Bgr	Bulgaria	BGR
Blt	Baltic states	EST, LTU, LVA
Bra	Brazil	BRA
Can	Canada	CAN
Che	Switzerland	CHE
Chl	Chile	CHL
Chn	China	CHN
Cze	Czech Republic	CZE
Deu	Germany	DEU
Dnk	Denmark	DNK
Egy	Egypt	EGY
Esp	Spain	ESP
Fin	Finland	FIN
Fra	France	FRA
FSU	Former Soviet Union	ARM, AZE, BLR, GEO, KAZ, KGZ, MDA, TJK, TKM, UZB
GBR	UK	GBR
Gulf	Gulf Countries	ARE, BHR, IRN, IRQ, KWT, OMN, QAT, SAU, YEM
Grc	Greece	GRC
Hrv	Croatia	HRV
Hun	Hungary	HUN
Idn	Indonesia	IDN
Ind	India	IND
Irl	Ireland	IRL
ita	Italy	ITA
jpn	Japan	JPN
Kor	Korea	KOR
MEast	Middle East	ISR, JOR, SYR, LBN, PSE
Mex	Mexico	MEX
Mys	Malaysia	MYS
Nld	Netherlands	NLD
NAfr	North Africa	ESH, TUN, MAR
NWAfr	North-West Africa	LBY, DZA
Nor	Norway	NOR
Ocean	Pacific Island	CXR, COK, HMD, NFK, NIU, NRU, PCN, TKL, TUV, UMI, WLF, FJI, PNG, FSM, GUM, ASM, TLS, PYF, KIR, MNP, MHL, NCL, PLW, WSM, SLB, TON, VUT, NZL
Pol	Poland	POL

Prt	Portugal	PRT
RCAm	Rest Central America	BES, CUW, SXM, ABW, BHS, BLZ, BRB, CRI, CUB, DMA, DOM, GRD, GTM, HND, HTI, JAM, LCA, NIC, PAN, SLV, TTO, VCT, BMU, SGS, TCA, VGB, VIR, AIA, ATG, BLM, CYM, GLP, KNA, MAF, MSR, MTQ, PRI
REur	Rest Europe	CYP, LUX, MLT, LIE, GRL, ISL, FRO, ALA, AND, GGY, GIB, IMN, JEY, MCO, SJM, SMR, VAT, SPM, BIH, ALB, MKD, MNE, SRB, KSV
Rou	Romania	ROU
RSAm	Rest South America	BOL, COL, ECU, FLK, GUF, GUY, PER, PRY, SUR, URY, VEN
RSAs	Rest South Asia	AFG, BGD, BTN, LKA, MDV, NPL, PAK
RSEAs	Rest South-East Asia	BRN, CCK, KHM, LAO, MMR, PHL, SGP, PRK, HKG, MAC, TWN, MNG
Rus	Russia	RUS
SSAfr	Sub-Saharan Africa	AGO, BEN, BWA, BFA, BDI, CMR, CPV, CAF, TCD, COM, COG, COD, CIV, GNQ, ERI, ETH, GAB, GMB, GHA, GIN, GNB, KEN, LSO, LBR, MDG, MWI, MLI, MRT, MUS, MYT, MOZ, NAM, NER, NGA, REU, RWA, STP, SEN, SYC, SHN, SLE, SOM, SSD, SDN, SWZ, TZA, TGO, UGA, ZMB, ZWE, DJI, IOT, BVT, ATF
Slo	Slovenia	SVN
Svk	Slovakia	SVK
Swe	Sweden	SWE
Tha	Thailand	THA
Tur	Turkey	TUR
Ukr	Ukraine	UKR
USA	USA	USA
Vnm	Vietnam	VNM
Zaf	South Africa	ZAF

2.B Proof of simplified impact specification

Lemma 1. *In an economic growth model with a Cobb-Douglas production function, stable capital-labor ratios, and "small" exogenous annualized growth rates* g_{it}*, the Burke, Hsiang and Miguel (2015) or similar damage function based on temperature-dependent annual growth impacts* δ_{it} *is approximately equivalent to using a damage function for a model with time step of* Δt *if we compute* Ω_{it}

as:

$$\Omega_{it} = (1 + \Omega_{it-\Delta t})\frac{1}{(1 + \delta_{it})^{\Delta t}} - 1 \tag{2.37}$$

Proof. With GDP given by $Y_{\text{GROSS},it} = \text{TFP}_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}$, as in eq. (2.1), we have that the per-capita growth factor equals to:

$$\frac{Y_{\text{GROSS},it}/L_{it}}{Y_{\text{GROSS},it-\Delta t}/L_{it-\Delta t}} = \frac{\text{TFP}_{it}}{\text{TFP}_{it-\Delta t}} \frac{(K_{it}/L_{it})^{\alpha}}{(K_{it-\Delta t}/L_{it-\Delta t})^{\alpha}}.$$

Given that historically, the capital-labour ratio in economies can be approximately considered very stable over time, we have that the annualized per-capita growth rate without climate impacts between t and $t + \Delta t$ can be computed as $(1 + \text{g}_{it})^{\Delta t} \approx \frac{\text{TFP}_{it}}{\text{TFP}_{it-\Delta t}}$. Now, based on the standard damage function in eq. (2.24), we have that $Y_{\text{NET},it} = \frac{Y_{\text{GROSS},it}}{1+\Omega_{it}}$ so that:

$$\frac{Y_{\text{NET},it}/L_{it}}{Y_{\text{NET},it-\Delta t}/L_{it-\Delta t}} \approx \frac{\text{TFP}_{it}}{\text{TFP}_{it-1}} \frac{1 + \Omega_{it-\Delta t}^{T}}{1 + \Omega_{it}^{T}}.$$

To obtain the equivalence to the annual growth rate impacts given by eq. (2.26), we need thus to solve the equation $(1 + \text{g}_{it} + \delta_{it})^{\Delta t} = (1 + \text{g}_{it})^{\Delta t} \frac{1+\Omega_{it-\Delta t}}{1+\Omega_{it}}$. Looking at the annualized growth rates, and since for growth rates and growth rate impacts of up to, say, 2% or 0.02, $\text{g}_{it} \approx 0$ and moreover $\delta_{it} \approx 0$, the left hand side is close and approximal to $\big((1 + \text{g}_{it})(1 + \delta_{it})\big)^{\Delta t}$. Therefore, the baseline growth factor drops out and we have $(1 + \delta_{it}) = \left(\frac{1+\Omega_{it-\Delta t}}{1+\Omega_{it}}\right)^{1/\Delta t}$. Solving for Ω_{it} we finally obtain:

$$\Omega_{it} = (1 + \Omega_{it-\Delta t})\frac{1}{(1 + \delta_{it})^{\Delta t}} - 1,$$

so that the standard damage factor used on consumption or GDP can be used, only in a recursive form. ■

We compared the resulting country-level impacts in the RCP8.5 with SSP5 baseline GDP projections as in Burke, Hsiang and Miguel (2015) and found correlations of 0.9998 in 2050 and 0.9858 in 2100 with the approximated implementation based on Lemma 1.

2.C Additional figures for qualitative calibrations

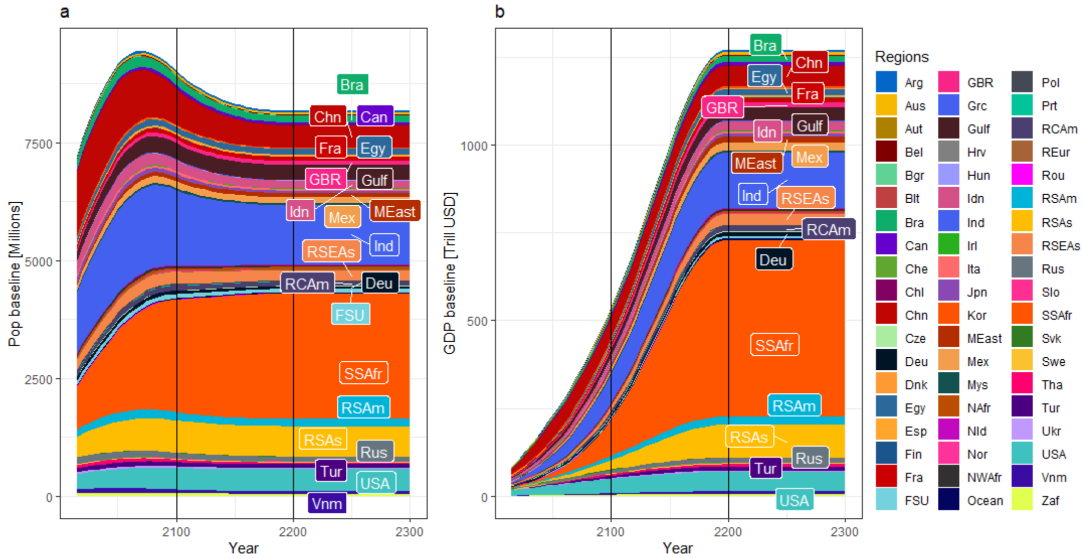

Figure 2.6: SSP2 scenario projections for regional population (a) and gross GDP [PPP] (b) over the full time horizon. Values from 2015 to 2100 are from SSP dataset. Values beyond 2100 are estimated according to the conservative approach described.

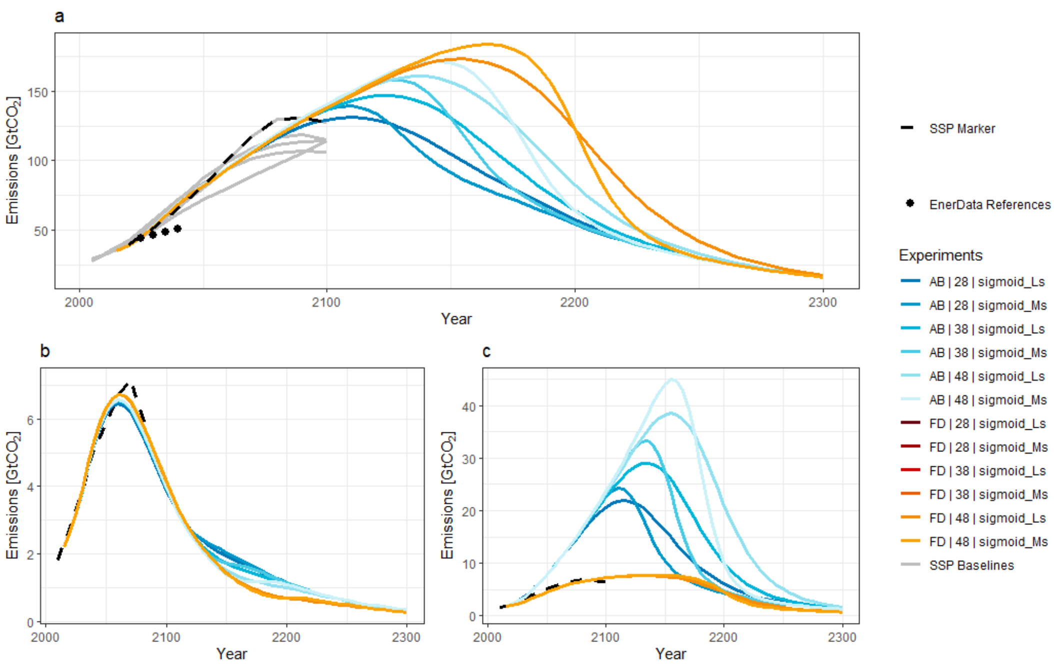

Figure 2.7: Examples of qualitative analysis for carbon-intensity calibration. In panel (a) are reported SSP2 emissions projections according to some experimental settings. Regional emissions under same settings are also reported for India under SSP1 (b) and Latin-America under SSP5 (c).

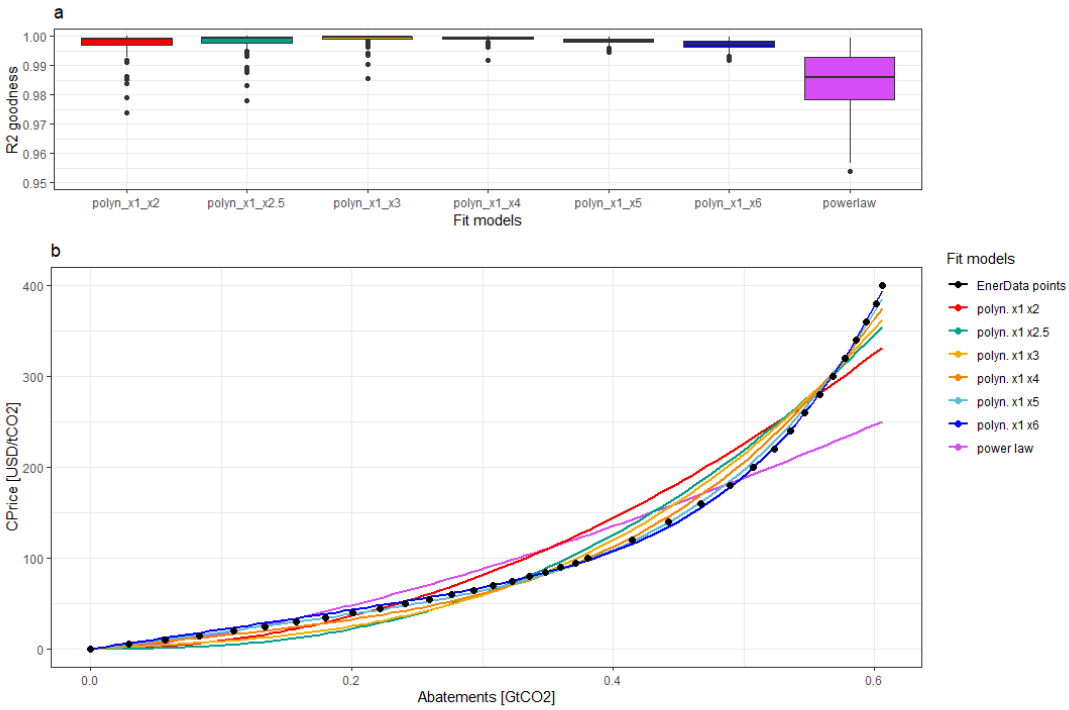

Figure 2.8: Panel (a) shows MACC fitting goodness (R-squared) distribution for each model tested. Panel (b) report an example of qualitative fitting analysis for China region.

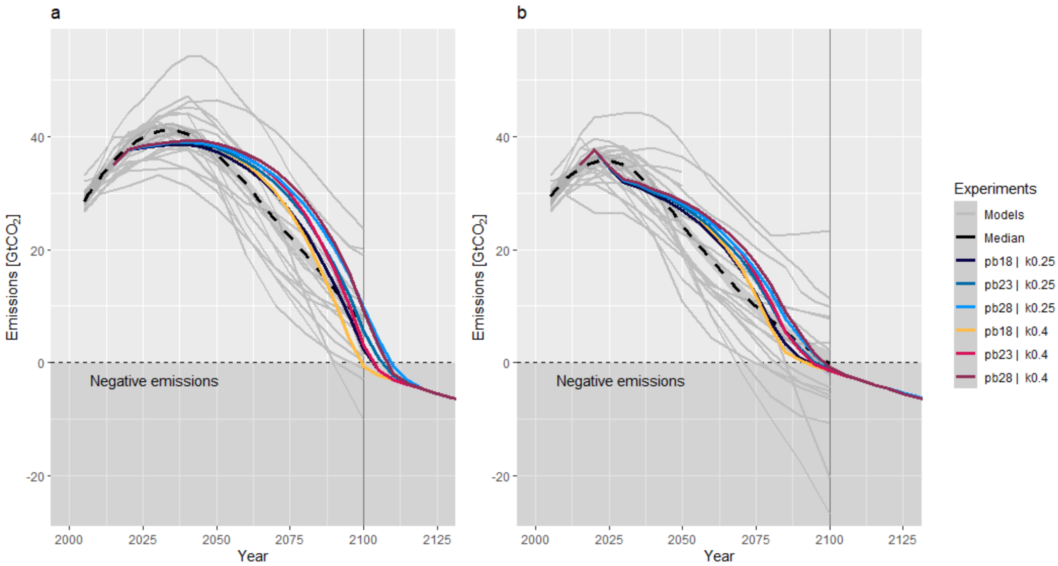

Figure 2.9: Figure showing qualitative analysis examples for MAC curves long-term transition towards backstop values. Resulting world emissions are compared with SSP-models references under same carbon-tax policies. In panel (a) carbon tax starts in 2020 from 30 US$ with 5% yearly growth. In panel (b) carbon tax starts from 80 US$ with 5% yearly growth. Experiments reported vary backstop converging time and transition smoothness.

Chapter

3 Persistent inequality in economically optimal climate policies[1]

3.1 Abstract

Benefit-cost analyses of climate policies by integrated assessment models have generated conflicting assessments. Two critical issues affecting social welfare are regional heterogeneity and inequality. These have only partly been accounted for in existing frameworks. In this chapter, we perform benefit-cost analysis using RICE50+, a model with more than 50 regions, calibrated upon emissions and mitigation cost data from detailed-process IAMs, and featuring country-level economic damages. We compare countries' self-interested and cooperative behaviour under a range of assumptions about socioeconomic development, climate impacts, and preferences over time and inequality. Results indicate that without international cooperation, global temperature rises, though less than in commonly-used reference scenarios. Cooperation stabilizes temperature within the Paris goals (1.80°C [1.53°C-2.31°C] in 2100). Nevertheless, economic inequality persists: the ratio between top and bottom income deciles is 117% higher than without climate change impacts, even for economically optimal pathways.

3.2 Introduction

Traditional benefit-cost analysis based on neoclassical Integrated Assessment Models (IAM) has often found limiting global warming to well-below 2 °C to be economically inefficient. In its standard set-up, the Dynamic Integrated Climate-Economy (DICE) model, the best-known benefit-cost IAM, suggests the economically optimal temperature to be 3.5 °C in 2100, and to peak above 4 °C amid next century (Nordhaus, 2018). This largely exceeds the UNFCCC Paris Agreement target (UNFCCC, 2015) and is close to what foreseen by detailed-process IAMs under lenient climate policies.

The DICE model has thus been subjected to several criticisms. Disputed points have been the choice of normative parameters such as the social rate

[1]This chapter is drawn from the paper "Persistent inequality in economically optimal climate policies" by P. Gazzotti, J. Emmerling, G. Marangoni, A. Castelletti, K.I. van der Wijst, A. Hof, M. Tavoni and published in *Nature Communications*: https://doi.org/10.1038/s41467-021-23613-y.

of time preference and the inter-temporal elasticity of substitution (Azar and Sterner, 1996; Cline, 1992; Stern, 2006), the specification of impact functions (Crost and Traeger, 2014; Sterner and Persson, 2007), the model's climate module (Van der Ploeg et al., 2020), and the mitigation cost structure (Mattauch et al., 2020; Weitzman, 2009). Thanks to being open-source and easily accessible, many studies have shown the model sensitivity to these factors.

Recently, few papers (Brown and Saunders, 2020; Glanemann, Willner and Levermann, 2020; Hänsel et al., 2020; Kalkuhl and Wenz, 2020) have amended DICE to consider the latest climate and economics science, including empirically-derived climate impact functions. The re-calibrated models have shown that the Paris agreement targets might be economically optimal under standard benefit-cost analysis. However, these findings rely on a single-region model, with no consideration of regional heterogeneity and inequality in the costs and benefits of climate action. This is a major limitation: one key finding of the empirical evidence about climate economic impacts is their high heterogeneity across countries (Burke, S. M. Hsiang and Miguel, 2015; Dell, Jones and Olken, 2012; Diffenbaugh and Burke, 2019; Kahn et al., 2019). Furthermore, emission reduction opportunities as estimated by detailed-process IAMs and reviewed by the IPCC vary significantly across countries (IPCC, 2018). Finally, aggregated benefit-cost analyses hide key sources of inequality, and these are consequently not accounted for in their welfare frameworks. The evidence from the benefit-cost assessments of heightened climate change impact doesn't yet account for regional heterogeneity. This prevents a comparison between cooperative and self-interested scenarios, accounting for preferences over equality, and fully capturing economic convergence dynamics and technological progress. Most importantly, it obscures inequalities across countries and leaves them out entirely from the optimization.

The benefit-cost literature has examined heterogeneity and inequality before. Ricke et al. (Ricke et al., 2018) provide a comprehensive analysis on social cost of carbon (SCC) at country-level resolution, while Taconet et al. (Taconet, Méjean and Guivarch, 2020) evidence how climate change affects inequality between countries under a large variety of scenarios. However, both do not perform any optimal evaluation. Benefit-cost IAMs such as RICE (Nordhaus, 2010; Nordhaus and Yang, 1996), AD-RICE (Bruin, Dellink and R. S. J. Tol, 2009), PAGE (Hope, 2008), FUND (Anthoff, 2009), CWS (Eyckmans and Tulkens, 2003), MICA (Lessmann et al., 2015), C^3IAM(Wei et al., 2020), and STACO (Nagashima et al., 2009), disaggregate the global economy in up to 6-16 macro-regions (see also the review by Weyant (Weyant, 2017)). This resolution allows only to partially capture the variation in the costs and benefits of climate action, and none of these models accounts for the latest climate and economic evidence. While other models, including Computable General Equilibrium (CGE) models such as in Dellink et al., 2014, provide sectoral and regional detail, their policy questions are in most cases evaluating prescribed policy pathways rather than inter-temporal optimization. Thus, albeit the topic has been addressed before, the proposed framework's improved granularity, calibration, and welfare specification represent novel steps.

We show that it is possible and advisable to go beyond traditional benefit-cost analysis centered on economic efficiency and to include heterogeneity and inequality as one of the key components of welfare. To do so, we have extended, regionalized and re-calibrated the DICE Integrated Assessment model to more than 50 independently modelled countries or regions, taking into account the latest evidence and data and expanding the social welfare function to include inequality aversion (see next section and Methods). The new model highlights international cooperation's relevance for achieving climate targets compliant with the Paris agreement. We also show and quantify how climate change increases global income inequalities even under welfare-maximizing policies and different socioeconomic pathways.

3.3 Results

RICE50+ model and scenarios

The modeling framework considers 57 independent regions (or countries, see Supplementary Information for the full list). The dynamics of economic growth, greenhouse gases (GHG) emissions, emissions mitigation costs, and economic impacts due to climate-change follow the well-known integrated assessment model DICE (the latest version of DICE-2016R2, used in Nordhaus, 2018). The regional representation is consistent with the finest granularity at which data, especially marginal abatement costs curves (MACC), is available. Socioeconomic drivers, including population and economics growth at the country-level, come from the five Shared Socioeconomic Pathways (SSP) (O'Neill et al., 2014; Riahi et al., 2017). Therefore, the model spans over five coherent alternative future socioeconomic development pathways.

The climate is modelled based on the original three-layered carbon-cyle structure, with exchange coefficients recalibrated to match the MAGICC6 model emulation (Meinshausen, Raper and Wigley, 2011). Radiative forcing and atmospheric temperature increase are also evaluated at the regional level through statistical downscaling calibrated on the CMIP5 database (Taylor, Stouffer and Meehl, 2011).

This framework allows us to directly introduce empirically-estimated climate impact functions at the country level, without the need to resort to aggregate-response fitting as in Glanemann, Willner and Levermann (2020). Climate, therefore, influences GDP growth according to local temperature variations. We use empirically-estimated non-linear impact functions which relate temperature increase to economic growth (Burke, S. M. Hsiang and Miguel, 2015). We consider all four major empirical specifications of Burke-Hsiang-Miguel (BHM). These include different time lags —capturing short-run (SR) and long-run (LR) impacts— and the extent to which rich and poor countries' income differentiation is accounted for. They also implicitly allow for different historical adaptation to climates. Furthermore, we carry out robustness analysis with alternative empirical impact function studies (Dell, Jones and Olken (2012) and Kahn et al. (2019)).

Emissions and marginal abatement cost curves are calibrated on multiple sources. For the near future (2025-2040), we use Enerdata-EnerFuture curves, based on the detailed-process based model POLES (Després et al., 2018), an energy sector model jointly developed with the European Commission. For the rest of the century, we use the information on emissions and abatement potential from detailed-process IAMs reviewed in the IPCC SR1.5 (IPCC, 2018). In the very long run (post-2100), model assumptions converge to DICE trends.

Constraints on emission reduction rates, due to the energy system inertia, and negative emissions availability follow Hänsel et al., 2020.

Regions maximize inter-temporal welfare. When acting in self-interest, countries act non-cooperatively and optimize their mitigation strategy taking others' behavior as given. Thus only own country climate impacts are optimized upon. The Nash equilibrium is found through an iterative algorithm. On the other hand, the cooperative setting implies a global social planner who maximizes a social welfare function that aggregates all regions' welfare. The implicit normativity of IAMs often doesn't include redistributive preferences. In contrast, our welfare specification disentangles inequality-aversion and inter-temporal inequity aversion. This allows capturing the essential issues of intertemporal and spatial inequality (see Anthoff and Emmerling (2019) and G. D. Atkinson et al. (2009) and the Methods section).

The geographical resolution, for both benefits and costs, and the expanded welfare function, allow us to explore the key sources of heterogeneity and inequality. These include the degree of cooperation (non-cooperative, cooperative), socioeconomic trends (SSP1 to SSP5, with SSP2 as default), four climate impact specifications (BHM-SR as default), and inequality aversion (γ). We span from inequality neutrality ($\gamma = 0$) to high inequality aversion ($\gamma = 2$), covering the full range suggested by A. B. Atkinson and Brandolini (2010). We choose $\gamma = 0.5$ as our default value, in accordance with several sources (R. S. Tol, 2010; U.S. Census Bureau, 2000). We also run alternative values for the utility discount rate ρ, varying over the interval 0.1% - 3% (1.5% as default). Unless otherwise stated, these values are adopted as default.

Global outcomes

Figure 3.1 summarises the world-aggregated model outcomes. The Business-As-Usual scenarios (*BAU no-impacts*), which assume no mitigation, project typically increasing emissions trends (Fig.3.1a). When climate impacts are factored in —a mechanism absent in the usual reference scenarios and yet relevant (Woodard, S. J. Davis and Randerson, 2019)— the lowered economic growth rate slightly reduces emissions (*BAU impacts*). This leads to a mean temperature increase at the end of the century of +3.65 °C [2.99 - 4.49 °C, 10th-90th percentile range] (Fig.3.1b). However, an adequate counterfactual scenario is when countries react to climate impacts based on their pure self-interest (here labelled as *Non-coop*). The non-cooperative scenario is characterized by relatively flat emissions, with an average 2100 temperature increase of +3 °C [2.10 - 4.19 °C] over pre-industrial levels. This result highlights the importance of an appropriate baseline, and corroborates recent criticisms of counterfactual scenarios having implausibly high emissions (Glen, 2016). A proper accounting of climate economic feedback generates significantly lower emissions and forcing than in the original SSPs (Riahi et al., 2017). Figure 3.1 also shows that if countries cooperated for the sake of the global good (*Coop*), fast emissions reductions would be optimal. Global carbon neutrality would be approached by mid-century. In most cases, these cooperative scenarios have a temperature increase below +2 °C [1.80, 1.53 - 2.31 °C]. These results confirm the recent DICE-based findings by Glanemann, Willner and Levermann

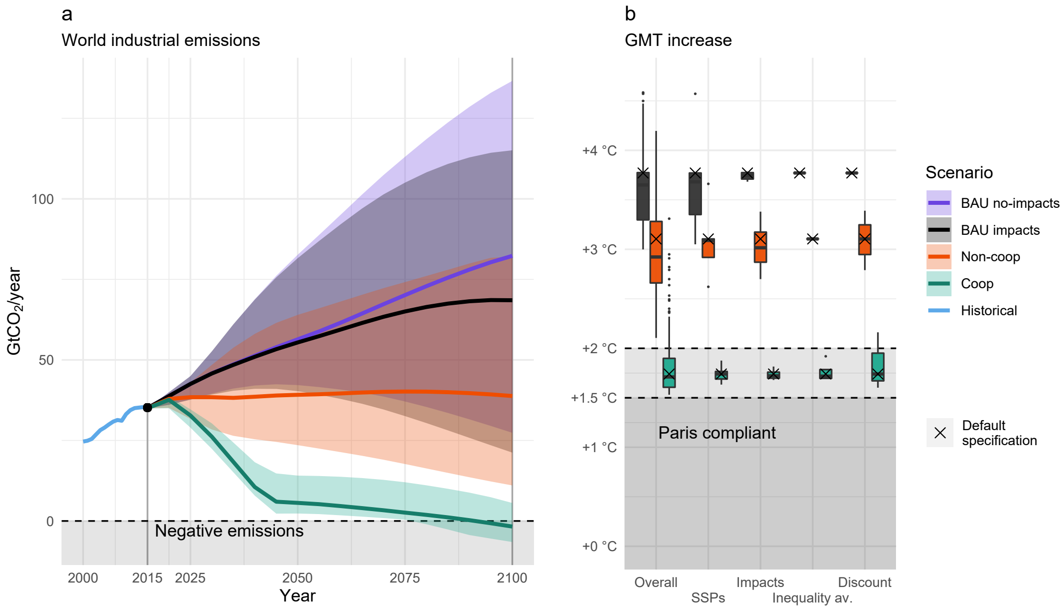

Figure 3.1: Optimal world-aggregated model outcomes. (a), Global CO2 emissions pathways. Uncertainty ranges include all SSPs and climate change impacts. (b), Global Mean Temperature (GMT) increase in 2100, and decomposed uncertainties ranges. *Overall* accounts for all the uncertainties. Other factors show temperature variability due to every single driver (with others fixed at their default level). Default specification (SSP2, BHM-SR impacts, utility discount rate of 1.5% and $\gamma = 0.5$) values are highlighted with a cross marker.

(2020) and Hänsel et al. (2020) in a regional setting. They also show that the Paris agreement's stricter interpretation of 1.5°C is not cost-optimal (Brown and Saunders, 2020). In terms of the uncertainty characterizing these global outcomes, Fig.3.1b summarizes the distribution of 2100 temperature increase, disentangling the contributions of every driver (with the others kept at their default level). Some sources of uncertainty, such as the normative decision of discount rate, equally affect both cooperative and non-cooperative outcomes. Others, such as socioeconomic pathways and climate impacts, have differentiated consequences, with non-cooperation showing wider outcome ranges. See also Supplementary Figure 3.15 for different uncertainty ranges in world-aggregated emissions.

Major economies and NDCs comparison

Figure 3.2 compares mitigation efforts and costs among selected major economies. Both cooperative and non-cooperative scenarios are reported for the policy-relevant time-frames of 2030 and 2050. In the absence of cooperation, emission reductions vary significantly across countries but are positive for most of them. Notably, large countries with relatively low mitigation costs and high expected climate impacts (India, followed by China and the U.S.)

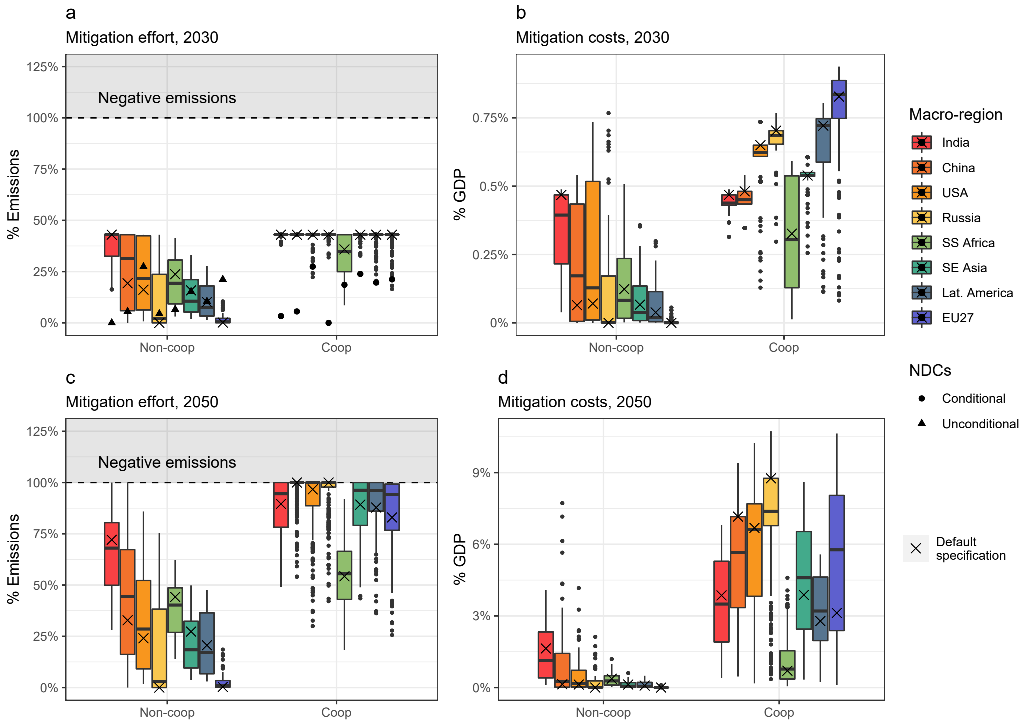

Figure 3.2: Major economies mitigation efforts and costs for cooperative and non-cooperative scenarios. (a-b), Distributions for year 2030 and NDCs pledges. (c-d), Distributions for year 2050. Mitigation efforts and costs are reported as the percentage of emissions reduced and percentage of GDP over BAU no-impacts reference. Macro-regions show the aggregated level from finer geographical-resolution results. Boxplot ranges include all scenarios explored. Default specification (SSP2, BHM-SR impacts, $\rho = 1.5\%$, and $\gamma = 0.5$) values are also highlighted.

mitigate emissions significantly out of pure self-interest. These countries cut CO2 between 20% to up to 75% of BAU emissions in 2050 (Fig.3.2c). Under full cooperation, all regions reduce emissions close to the maximum potential, except Sub-Saharan Africa which starts at very low emissions per-capita level. This is consistent with mitigation efforts in the major world economies aiming at climate stabilization (M. Tavoni et al., 2015). We compare the regional emissions with the pledges made by countries in the Paris Accord for 2030. National Determined Contributions (NDCs), as estimated by (Hof et al., 2017) and (Elzen et al., 2016) and reported in Fig.3.2a, are closer to non-cooperative ranges. Notable exceptions are India (conditional NDC target estimated around 10% of reductions, lower than its optimal self-interest effort) and EU27 (aiming at least 25% of reductions, with even higher ambitious decarbonization programs under consideration), which are closer to — but still lower than — cooperative levels. On the other hand, cooperation demands higher ambition than the NDCs for all regions, supporting a ratcheting up of the current pledges (Rogelj et al., 2016). Emission reductions translate into costs (Fig.3.2b and d), depending on the intensity of the mitigation effort and regional abatement opportunities. In 2030, GDP losses are negligible, but they increase to up to 10% in 2050 for

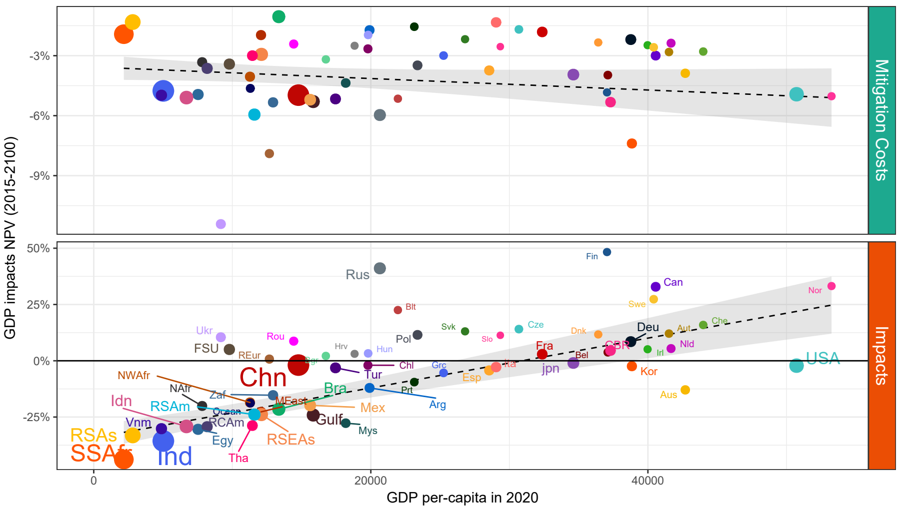

Figure 3.3: GDP net-present-value impacts and costs against current GDP per-capita. NPV is evaluated for interval 2015-2100, with world-average Ramsey yearly discount rate. Reported scenario is cooperative, SSP2, under BHM-SR impact function and intermediate levels for inequality aversion ($\gamma = 0.5$) and utility discount rate ($\rho = 1.5\%$).

the most exposed regions (i.e. Russia). The heterogeneity of mitigation costs related to, among other factors, the carbon intensity of the economy has been documented with detailed-process IAMs (M. Tavoni et al., 2015). Additional details for important regions such as the Middle East and individual countries are shown in Supplementary Figure 3.6.

Persistent inequality

Turning to equity considerations, Figure 3.3 shows the distributional effects of costs and impacts for globally cooperative scenarios. Mitigation costs are spread relatively uniformly across countries' income levels (for the default value of inequality aversion). However, climate change impacts are highly regressive. The poorest countries (representing the largest share of the world population, as indicated by the bubble size) face dramatic economic losses, exceeding 20% of GDP. Indicatively, economic impacts increase by 11 percentage points for every 10,000 Dollars reduction in per-capita GDP. Note that this happens despite the strong collective effort to reduce emissions, which, as we have seen, allows to keep temperature below 2°C.

As reported in Supplementary Figure 3.9, different inequality aversion parameters lead to markedly different regional mitigation efforts. For every 10,000 Dollar lower GDP level, mitigation costs ranges from an increase by 0.2 ($\gamma = 0$) to a decrease by 0.6 ($\gamma = 1.45$) GDP percentage points. Supplementary Figure 3.13c relates the choice of inequality aversion to per-capita emissions, thus connecting the welfare representation of preferences over equity to the debate about burden-sharing. Variation in inequality preferences leads to

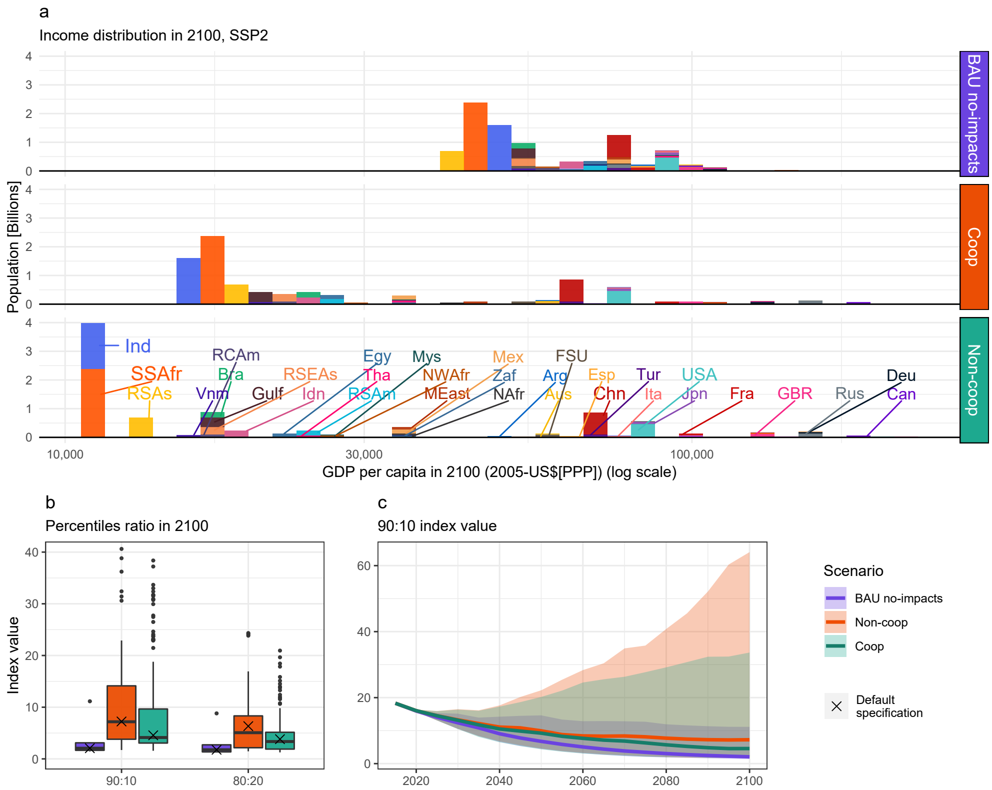

Figure 3.4: Income distribution and inequality indexes. (a), GDP per-capita, net of costs and impacts, population-weighted distribution in 2100 under our default specification. (b), 90:10 and 80:20 inequality index (percentile-ratios over population-weighted distributions), in 2100, of all scenarios. Year 2020 values are 15.9 (90:10 ratio) and 3.2 (80:20 ratio). (c), 90:10 index evolution over time among all scenarios (The scenarios based on the SSP2 pathway are shown as solid lines).

vastly different per-capita emissions, consistent with commonly discussed burden-sharing principles such as equality per-capita. Yet, globally aggregated emissions and resulting temperature are relatively unchanged, as shown in Figure 3.1b. Thus, climate damages remain highly regressive independently of equity preferences; these mostly affect mitigation efforts and costs.

This analysis is robust also across different climate impact specifications (see Supplementary Figure 3.8). These results show that global aggregated impacts may be misleading, given the wide range of expected impacts (between -50% and +50%), even in the most optimistic cooperative scenario (roughly compliant with the Paris target).

Further evidence on the persistent inequalities in economically optimal pathways is reported in Figure 3.4. It highlights how climate change stretches the income distribution between countries. The shift towards poorer levels affects most of the world population, while a smaller number of countries gain.

The reason for this is the non-linearity of climate impacts with temperature. Despite being affected by lower local temperature increases than higher-latitude countries, being already far from the optimal temperature (estimated around 13°C by (Burke, S. M. Hsiang and Miguel, 2015)) results in heightened damages for warmer regions (see Fig.3.5). The consequence is that 2.3 and 1.6 billion of African and Indian citizens respectively see their income drop by up to 60%. Climate-driven inequalities are significant even under globally optimal scenarios. Due to climate change, the ratio between top and bottom income deciles (90:10 ratio) and quintiles (80:20 ratio) increases by 117% and 63% respectively in the cooperative scenario (panel b, Figure 3.4). This adds to warming already observed today, which has led to an increase of the top-bottom income decile ratio of 25% (Diffenbaugh and Burke, 2019) (although calculated at a finer regional scale). An extra degree of warming has a more-than-proportional effect on global inequality due to the non-linearity of climate economic impacts (see Supplementary Figure 3.14). The inequality ratio improves over time (panel c, Figure 3.4) thanks to global economic convergence; growing uncertainties however accompany this projection.

The relevance of the underlying socioeconomic development is shown in Supplementary Figure 3.11. Inequality trends are coherent with the socioeconomic storylines and assumptions about economic catch-up between developing and industrialized countries. Climate increases economic inequality consistently across SSPs. Under SSP4, a pathway characterized by persistent inequalities, the inequality indexes at the end of the century are higher than today (by 40% for the 90:10 ratio). In SSP1, characterized by a low emission and economically equitable outlook, inequality improves over today (by 79% for 90:10); but remains below where it would have been without climate change (90% reduction). Failure to globally cooperate on emission reductions increases inequality, by more than doubling the income ratios. Result are robust across different impact specifications (as shown in Supplementary Figure 3.12) and alternative levels of inequality aversion (as shown in Supplementary Figure 3.13). Compared to no-climate-change BAU, only under BHM-LR assumption, which projects higher losses and affects all the countries, we observe cooperation leading to small improvements (about -5.3%); in all other cases, it worsens more than ten times in magnitude. Lower tolerance for inequality in the welfare specification improves inequality only marginally, as reported in Supplementary Figure 3.13.

Taken together, these results project climate-induced inequalities both under self-interested and cooperative behaviour and preferences for equality. The main determinant of this result is the climate impact-functions and their non-linear response to local temperature increases, which determine long-lasting economic growth reductions. Consequently, and together with the inertia in the mitigation ramp-up speed, emission reductions start bearing a visible effect on temperatures only around 2050 and beyond (see Supplementary Figure 3.10b). The combined effect of historical emissions and those occurring in the few coming decades is sufficient to irreversibly increase inequality between countries and lead to strong climate impacts even if global cooperation is achieved, as shown in Fig.3.5. This result is robust to alternative impact specifications (as shown in Supplementary Figure 3.7). Moreover, if full cooperation is delayed to 2030, a more realistic outcome consistent with the current pledges, inequality

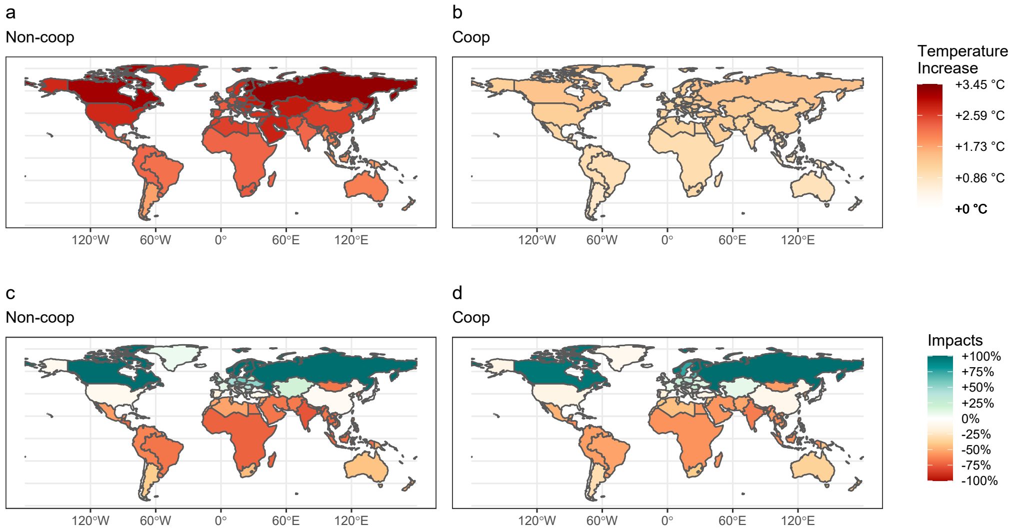

Figure 3.5: Map of population-weighted temperature increases and climate impacts projected in 2100. (a-b), Local temperature increases are compared to the 1980-2010 average. (c-d), Impacts [% of GDP] projected for the year 2100. All scenarios use the default specification.

would further increase (from an average of +117 % to +148% for the 90:10 ratio over baseline values, see Supplementary Figure 3.10). Note that we did not model within-country inequality in our analysis. Adding this additional level of disaggregation, as indicated, e.g., by Dennig, Budolfson et al. (2015) and S. Hsiang et al. (2017), would increase global inequalities.

3.4 Discussion

The regional-detailed and welfare-expanded benefit-cost analyses provide a broader, more burdened, perspective of the evolving climate. We provide new insights into the distributional implications for a wide array of scenarios and preferences parameterization. Regional detail allows us to systematically explore international cooperation, socioeconomic assumptions, impact function specifications, discounting assumptions, and most importantly inequality aversion. The analysis is a first, modest step towards broadening human welfare accounting into IAMs; nonetheless, the unit of analysis remains coarse compared to pressing social issues such as poverty and other forms of discrimination.

Results confirm the economic optimality of the 2 degrees goal in a regionally disaggregated setting. However, this result is obtained solely under assumptions of full cooperation and immediate action, highlighting the need of high institutional capacity to attain the Paris agreement (Brown and Saunders, 2020). We show that rich nations take on more stringent mitigation effort under sufficient redistribution preferences towards poorer countries. Thus, we relate welfare analysis to burden sharing equity principles. However, due to geographical distribution and persistence of climate economic impacts, climate change increases inequality. This can only be partially reduced by mitigation action. Even under optimistic assumptions about international climate agreements and how much the world cares for inequality, climate change regressive impacts persist.

These results lead to policy recommendations about time left for useful action. Besides increasing mitigation efforts and fostering cooperation, efforts should also go towards developing alternative climate policy strategies. These include CO2 removal technologies, if deployed at scale and relatively fast, or, possibly, geoengineering strategies (Harding et al., 2020). Existing assessments from detailed-process IAMs typically foresee the use of CO2 removal in the second half of the century (IPCC, 2014), (Realmonte et al., 2019), with negative repercussions for inter-generational equity (Emmerling, Drouet et al., 2019). Our analysis suggests that if climate change impacts are persistent as estimated by (Burke, S. M. Hsiang and Miguel, 2015) and others, then CO2 removal should be anticipated and used earlier to complement traditional emission reduction options. Resilient socioeconomic development and adaptation planning and financing, particularly in the worst affected countries, will help manage the increased disparities brought about by climate change. Besides acting on emission reductions, mechanisms to compensate climate-induced inequalities and promote inclusive socioeconomic development are needed.

Finally, it is worth mentioning the potential limitations of empirical impact functions over long timescales. They are based on historical observations and may misrepresent future economic responses and adaptation to temperature variability (see also Burke, W. M. Davis and Diffenbaugh, 2018). Moreover, many relevant dimensions of heterogeneity are not represented within this relatively simple model. These include socioeconomic impacts and sectoral detail on the energy system, land-use changes and agriculture, and biodiversity and nature. While many of these impacts have been implemented in process-based IAMs, other dimensions are still absent from the analysis. These include multifaceted inequalities (e.g. race, basic human needs, gender, see Emmerling and Massimo Tavoni, 2021), interactions with environmental risks (such as health), adaptation (such as adaptive capacity) and mitigation efforts (e.g., due to unequal patterns of consumption). The current paper has shown that socially relevant theoretical frameworks can be operationalized and can highlight the need for novel solutions. More work is needed to incorporate inequality in model-based assessment of climate change.

3.5 Methods

Regional aggregation

Regions in RICE50+ model are based on the finest regional disaggregation of the POLES-EnerData abatement costs data. We kept European Union and G20 countries with country-level decision making, while others are grouped into larger macro regions. These include gulf Arabic states (golf57), former Soviet-Union (ris), middle-East group (osea), and minor countries from South-East-Asia (rsas), Latin-America (rsam), and Sub-Saharan Africa (rsaf).

Economy

RICE50+ largely inherits from the Nordhaus DICE model its economic representation. GDP output is computed, for each region i, via a Cobb-Douglas production function of capital $K_i(t)$ and labour $L_i(t)$, with total factor productivity $\mathrm{TFP}_i(t)$:

$$Y_{\mathrm{GROSS},i}(t) = \mathrm{TFP}_i(t) \cdot K_i(t)^{\alpha} \cdot L_i(t)^{1-\alpha}. \tag{3.1}$$

We consider labour and TFP projections exogenous, and calibrate them to match, in the BAU case, the Shared Socioeconomic Pathways (SSPs) population and GDP pathways (Riahi et al., 2017). Since SSPs data cover 2015-2100 period only, beyond 2100 we extended the projections by linearly extrapolating the last growth rate, progressively reducing it towards zero in 2200 so that from 2200 GDP and population stabilize.

In DICE/RICE models, savings rates $S_i(t)$ are usually left as free variables to be optimized. They determine investments and capital accumulation according to equations:

$$I_i(t) = S_i(t) \cdot Y_i(t) \tag{3.2}$$

and:

$$K_i(t+1) = (1-\delta_k)^{\Delta t} \cdot K_i(t) + \Delta t \cdot I_i(t). \tag{3.3}$$

Variable $Y_i(t)$ is the final GDP resulting after subtracting abatement costs $\Lambda_i(t,\mu_i)$ to GDP net-of-damages $Y_{\mathrm{NET},i}(t)$:

$$Y_i(t) = Y_{\mathrm{NET},i}(t) - \Lambda_i(t,\mu_i). \tag{3.4}$$

The optimization of savings rates wasn't affecting the results in a relevant way for present analysis, while it substantially increased model complexity and computational time. Moreover, when optimizing with endogenous savings rate, the model must include a simpler approximation (eq.3.19) for impacts (described later in impacts section). Hence, we opted for fixing the savings rates, starting from historical values and linearly converging to the DICE-2016R2 long-term projection $\overline{S}$ by the year 2200. In Supplementary Figure 3.16 endogenous and fixed savings rate results are compared for representative scenarios. Panel a and b show how endogenous savings lead to slightly lower global emissions and temperatures. However, panel c, confirms inequality results across all SSPs scenarios (with a noteworthy exacerbation for endogenous savings in SSP4 —persistent inequality pathway— deciles indexes). Thus, the main results about inequality are confirmed or exacerbated when endogenizing saving rates.

Emissions calibration

Baseline industrial emissions are directly related to economies output through the exogenous carbon-intensity $\sigma_i(t)$, expressing fossil-fuel-shares in economic production:

$$E_{\mathrm{IND},i}(t) = \sigma_i(t) \cdot Y_{\mathrm{GROSS},i}(t) \cdot (1 - \mu_i(t))\,. \tag{3.5}$$

To calibrate it, we followed a two-step process. First we calibrated SSP2 projections, starting from the DICE dynamics:

$$\sigma_i(t+1) = \sigma_i(t) \cdot \exp\big(g_i(t) \cdot \Delta t\big). \tag{3.6}$$

We imposed 2015 historical levels, and estimated $\overline{\sigma_i}(t)$ values that minimize the difference between resulting emissions, EnerData baselines (available for 2025-2040 period), and regional levels from SSP2-marker-model (Message-GLOBIOM).

Beyond 2100 we opted for a smooth convergence, for each region, to DICE-2016R2 global carbon intensity levels by year 2200. At each point in time carbon intensity is the result of a convex-combination of two components:

$$\sigma_{ssp2,i}(t) = \big(1 - \mathrm{cc}(t)\big) \cdot \overline{\sigma_i}(t) + \mathrm{cc}(t) \cdot \sigma_{\mathrm{DICE}}(t), \tag{3.7}$$

with coefficient $\mathrm{cc}(t)$ following a smooth sigmoid transition from 0 to 1 for $t \in [2100, 2200]$.

Then, we evaluated carbon intensities for the other SSPs by including an SSP-dependent, region-independent, multiplier $m_i(ssp)$ in equation (3.6), including previously-optimized $\overline{g_i}(t)$ term:

$$\sigma_i(ssp, t+1) = m_i(ssp) \cdot \sigma_i(ssp, t) \cdot \exp\big(\overline{g_i}(t) \cdot \Delta t\big). \tag{3.8}$$

As before, we fixed 2015 levels and computed $\hat{m}(ssp)$ values that minimize differences between projected emissions and regional emissions for each SSP-Marker model. Beyond 2100 we kept the convex combination between calibrated curves and DICE global carbon intensity.

Abatement costs

Regions optimize the fraction of baseline emissions to abate, $\mu_i(t)$, in the range $[0, 1.2]$, with an abatement greater than 1 corresponding to negative emissions. We evaluated region-specific abatement costs curves starting from the Enerdata dataset, which includes industrial CO2-abatement levels for several carbon prices over the 2025-2040 time period. We fitted the data to find the best representative continuous MAC curve. Comparing R-squared goodness-of-fit measures, we selected the best candidate, a fourth-exponent polynomial curve:

$$\mathrm{MAC}_i(t, \mu) = a_i(t)\mu_i + b_i(t)\mu_i^4. \tag{3.9}$$

After calibrating region-specific coefficients, we added a multiplier correction-factor $\nu(t)$, equal for each region, to better match these curves to the state-of-the-art assumptions in the Integrated Assessment Modelling community. We used policy scenarios with carbon prices projections from SSPs database to extract several MAC curves. We used those curves to find the best value $\overline{\nu}(t)$, which minimizes the difference between RICE50+ global emissions abated and the SSP ensemble's median levels.

After 2100, we extend last data-fitted regional curves, and use same correction-factor $\nu(t)$ to lead a progressive convergence towards a common backstop-technology curve BT(t), which follows the original DICE-2016R2 definition. The transition phase begins after 2040 and lasts until time t_{BT}, when each region starts matching the original backstop values for a 100% mitigation level $\hat{\mu_i}$:

$$\nu(t) \cdot \left(a_i(t)\hat{\mu_i} + b_i(t)\hat{\mu_i}^4 \right) = BT(t) \mid_{t \geq t_{\mathrm{BT}}} . \tag{3.10}$$

Regional total mitigation costs Λ are then linked to its mitigation level $\mu_i(t)$ according to the equation:

$$\Lambda_i(t, \mu_i) = \int_0^{\mu_i} E_{\mathrm{BAU},i}(t) \cdot \mathrm{MAC}_i(t, \mu_i)\, d\mu \tag{3.11}$$

and therefore:

$$\Lambda_i(t, \mu_i) = \nu(t) \cdot E_{\mathrm{BAU},i}(t) \cdot \left(\frac{a_i(t)}{2}\mu_i^2 + \frac{b_i(t)}{5}\mu_i^5 \right) \tag{3.12}$$

Differently from the original DICE formulation, we constrain the maximum mitigation increase rate over time to reflect inertia in mitigation technologies. Following Hänsel et al. (2020) we set a 20% maximum increase every 5-years period:

$$\mu_i(t+1) \leq \mu_i(t) + 0.2. \tag{3.13}$$

Global and local climate

The concentration of greenhouse gases is modelled through a three-box carbon sink model. Radiative forcing RF(t) is computed based on the changes in its concentration $M_{CO_2}(t)$ from pre-industrial levels $M_{CO_2,\mathrm{pre}}$, and the exogenous addition of Other-GHG contribution:

$$RF(t) = \alpha \times \left(\ln(M_{\mathrm{CO_2}}(t)) - \ln(M_{\mathrm{CO_2},pre}) \right) + RF_{\mathrm{OGHG}}(t) \tag{3.14}$$

with $\alpha = 5.35$. The global atmospheric temperature increase ΔGMT(t) is computed following the DICE-2016R2 two-layer model, re-calibrated in its exchange-coefficients to match the MAGICC6 behaviour (Meinshausen, Raper and Wigley, 2011).

To perform the impact evaluation at the country or regional level at great detail, regional temperature responses are also needed to properly consider the significant heterogeneous warming response. To this end, we implemented a statistical downscaling method based on the CMIP5 database (Taylor, Stouffer and Meehl, 2011). It provides historical data and projections of temperature and precipitation at the 0.5° gridded level. We aggregated values to the country and year average level using population weights, obtaining data for $N = 244$ countries and territories. Finally, we used the global temperature data from the different representative concentration pathways (RCPs), implemented by several global climate models. We considered the median of the model ensemble to link global mean temperature increase (ΔGMT) to the country-level average annual temperature for all the RCPs.

Based on this data set, we run a linear regression to estimate the local temperature levels in region i at time t (denoted as $T_i(t)$ and measured in °C) as a consequence of global temperature increase $\Delta\text{GMT}(t)$:

$$T_i(t) = \alpha_i + \beta_i \Delta\text{GMT}(t) \tag{3.15}$$

The R^2 of the estimated regressions varies between 0.95 and 0.999. Finally, we aggregated country-level estimates to get the values (α_i, β_i) for the 57 model regions.

Implementation of growth impacts

While the original DICE and other similar IAMs implement damages based on the level of GDP per period, we implemented different empirically calibrated specifications (*spec*) of linear impacts on the per-capita growth rate $\delta_{i,\text{spec}}(t)$. This factor is then applied to the GDP per-capita growth rate $\mathrm{g}_i(t) = \frac{Y_{\text{NET},i}(t)}{L_i(t)} / \frac{Y_{\text{NET},i}(t-1)}{L_i(t-1)} - 1$:

$$\frac{Y_{\text{NET},i}(t)}{L_i(t)} = \frac{Y_{\text{NET},i}(t-1)}{L_i(t-1)} \big(1 + \mathrm{g}_i(t) + \delta_{i,\text{spec}}(t)\big). \tag{3.16}$$

By combining this impact function specification with the traditional impact definition in DICE given by

$$Y_{\text{NET},i}(t) = \frac{Y_{\text{GROSS},i}(t)}{\Omega_i(t)}, \tag{3.17}$$

and equations (3.1), (3.2), and (3.3), we obtained a new recursive formula for impacts $\Omega_i(t)$:

$$\Omega_i(t+1) = \frac{\text{TFP}_i(t+1)}{\text{TFP}_i(t)} \left(\frac{L_i(t+1)}{L_i(t)}\right)^{-\alpha} \cdot \Upsilon_i\big(t\big)^{\alpha} \cdot \frac{1 + \Omega_i(t)}{\big(1 + \mathrm{g}_i(t) + \delta_{i,\text{spec}}(t)\big)^{\Delta t}} - 1, \tag{3.18}$$

where:

$$\Upsilon_i\big(t\big) = (1 + \delta_k)^{\Delta t} + \Delta t \cdot S_i(t) \cdot \text{TFP}_i(t) \cdot \left(\frac{L_i(t)}{K_i(t)}\right)^{1-\alpha} \cdot \frac{1}{1 + \Omega_i(t)}.$$

While this implementation is perfectly consistent with the growth-rate empirical estimation, it can lead to numerical issues, in particular when the savings rate is endogenous. Therefore, in this case we implemented also an approximate equivalent rule to the standard $\Omega_i(t)$ as in DICE. In an economic growth model with a Cobb-Douglas production function, stable capital-labor ratios, and "small" exogenous annualized growth rates g_{it}, the Burke, S. M. Hsiang and Miguel (2015) or similar damage function based on temperature-dependent annual growth impacts δ_{it} is approximately equivalent to the following recursive formula:

$$\tilde{\Omega}_i(t+1) = (1 + \tilde{\Omega}_{it}) \frac{1}{\big(1 + \delta_{i,\text{spec}}(t)\big)^{\Delta t}} - 1. \tag{3.19}$$

The analytical proof an further discussion are reported in (Gazzotti, 2021).

Lastly, cumulative growth impacts can lead to very high positive or negative impacts over three centuries for some small countries. To avoid this degenerating trend and the risk of biasing model optimal decisions, we limited GDP impacts within a $[+100\%, -100\%)$ interval with respect to the baseline.

Burke et al. (2015) impact function

The regional temperature patterns allowed us to integrate an impact function based on Burke, S. M. Hsiang and Miguel (2015). Using long-run estimates and a single equation for all countries, the authors obtained a function of growth effects directly related to country-level temperature $T_i(t)$:

$$\mathrm{h}\big(T_i(t)\big) = 0.0127 \cdot T_i(t) - 0.0005 \cdot T_i(t)^2. \tag{3.20}$$

Impacts $\delta_{i,\mathrm{BHM}}(t)$ on the production growth rate are computed as the difference between the value of this function at time t and its value at the reference average temperature between 1980 and 2010 T_{i0}:

$$\delta_{i,\mathrm{BHM}}(t) = \mathrm{h}\big(T_i(t)\big) - \mathrm{h}\big(T_{i0}\big). \tag{3.21}$$

Dell, Jones and Olken (2012) impact function

In the paper by Dell, Jones and Olken (2012), another linear relationship between temperature and economic growth is estimated. The parameter $\delta_{i,\mathrm{DJO}}(t)$ yields the following main specification based on a (almost insignificant) general effect, and a strong negative effect of about additional 1.655 percentage point reductions in growth for poor countries (i.e., having GDP per-capita [PPP] below the median in the base year):

$$\delta_{i,\mathrm{DJO}}(t) = 0.00261 \cdot \Big(T_i(t) - T_{i0}\Big) - 0.01655 \cdot \Big(T_i(t) - T_{i0}\Big) \mathbb{1}_{\mathrm{GDP}_{\mathrm{CAP},i}(t_0) < Median(\mathrm{GDP}_{\mathrm{CAP},i}(t_0))} \tag{3.22}$$

Kahn et al. (2019) impact function

A third empirical paper by Kahn et al. (2019) similarly estimates a linear relationship, but differentiated for increases and decreases of the country-level temperatures over the historical norm. Using their main specification with $n = 30$ years for computing the historical norm as moving average (in our case starting from 1980-2010 in consistency with the case of Burke, S. M. Hsiang and Miguel (2015)), we obtain a third specification for the growth effect $\delta_{i,\mathrm{Kahn}}(t)$. Their main results conclude that a temperature increase by one degree over the historical norm is associated with a growth rate reduction by 5.86 percentage points. In comparison, a decrease by one degree implies a reduction of growth by 5.20 percentage points. The authors don't find significant difference between rich and poor countries.

$$\begin{aligned}\delta_{i,\mathrm{Kahn}}(t) = &-0.0586\Big(\big[T_i(t) - \overline{T}_i(t-1)\big] - \big[T_i(t-1) - \overline{T}_i(t-2)\big]\Big)\mathbb{1}_{T_i(t) > \overline{T}_i(t-1)} \\ &-0.0520\Big(\big[T_i(t) - \overline{T}_i(t-1)\big] - \big[T_i(t-1) - \overline{T}_i(t-2)\big]\Big)\mathbb{1}_{T_i(t) < \overline{T}_i(t-1)}\end{aligned} \tag{3.23}$$

with $\overline{T}_i(t-1) = n^{-1}\sum_{\tau=1}^{n} T_i(t-\tau)$ for $n = 6$ (each t accounts for 5 years).

Welfare

In the original RICE model, the social welfare function is specified as follows:

$$W = \sum_i \sum_t w_i(t) \cdot L_i(t) \cdot \left(\frac{\left(C_{\mathrm{CAP},i}(t)\right)^{1-\eta} - 1}{1-\eta} - 1 \right) \cdot (1+\rho)^{-t} \tag{3.24}$$

While Negishi weights $w_i(t)$ have been used in the regional RICE model, their distortion of inter-temporal preferences has been criticized and their welfare economic implications are at odds with welfare economics (see, e.g., Dennig and Emmerling (2017) and Stanton (2010)). We therefore implemented an alternative welfare function that has as special cases the standard welfare function, while on the other end replicating the idea of simply maximizing global consumption (as proposed in Stanton (2010) as one solution), and allows a gradual change from equal marginal utility to population weighting. This is implemented through an additional parameter of inequality aversion γ in the welfare specification (see also Berger and Emmerling, 2020):

$$W = \sum_{t=1}^{T} \left[\frac{1}{1-\eta} \left(\sum_i w_{\mathrm{pop},i}(t) \left(\frac{C_i(t)}{L_i(t)} \right)^{1-\gamma} \right)^{\frac{1-\eta}{1-\gamma}} - 1 \right] \cdot (1+\rho)^{-t} \tag{3.25}$$

with population-weights $w_{\mathrm{pop},i}(t) = L_i(t)/\left(\sum_i L_i(t)\right)$ and $\gamma \neq 1$ condition. Here, ρ denotes the utility discount rate, set to 1.5% in our default specification equal across regions and over time, while, as in DICE, we use $\eta = 1.45$ as inverse of the inter-temporal elasticity of substitution, which is close to what an expert elicitation on this parameter has found (Drupp et al., 2018). For $\gamma = 0$, the objective becomes to maximize world average consumption while for $\gamma = \eta$, the formulation collapses to the standard DICE welfare function. For the value of γ, A. B. Atkinson and Brandolini (2010) consider values between 0.2 and 2.5 as defensible. For our default specification we chose an intermediate value of $\gamma = 0.5$, e.g., close to the value found in R. S. Tol, 2010 or values used in U.S. Census Bureau, 2000).

Other GHGs and Land-Use

We kept Land-Use (LU) and other greenhouse gases (OGHG) as exogenous addition to the main model dynamics. For Land-Use, we retrieved regional starting levels $E_{LU,i}(t_0)$ from the country-level PRIMAP-hist database (Gütschow et al., 2016). We took the mean values between 2010 and 2015 to average out historical fluctuations, common in LU emissions. We kept original DICE-2016R2 decreasing trend and differentiated between two alternative cases. In the first one, used for BAU scenarios, all countries are affected by the decreasing trend. This will lead high-emitting countries to lower their emissions over time and countries that already start from negative values to increase their emissions towards the common zero-value asymptote. In the second case, used for benefit-cost scenarios, we apply this reduction only to those countries that start from positive values, keeping constant negative ones.

For the OGHGs, we retrieved data from SSPs models comparing relative forcing contribution RF_{OGHG} to the forcing from CO_2 (RF_{CO_2}). Given that we found a relatively close linear relationship ($R^2 = 0.608$) between both global forcing contributions and across all scenarios, we added OGHGs using the regression-estimated parameters ($\text{slope} = 0.199, \text{intercept} = -0.011$) in the model.

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3.7 Data Availability

All data generated and used in this analysis can be accessed at https://github.com/witch-team/RICE50xmodel/releases/download/v1.0.0/NC2021_results_dataset.zip

3.8 Code Availability

All code generated and used in this analysis can be accessed at https://github.com/witch-team/RICE50xmodel

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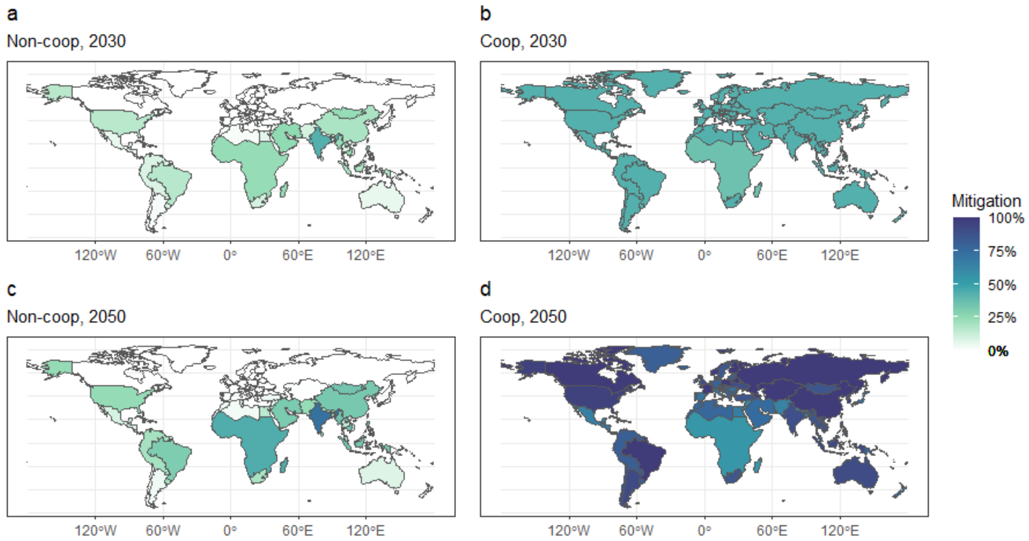
3.A Model regions

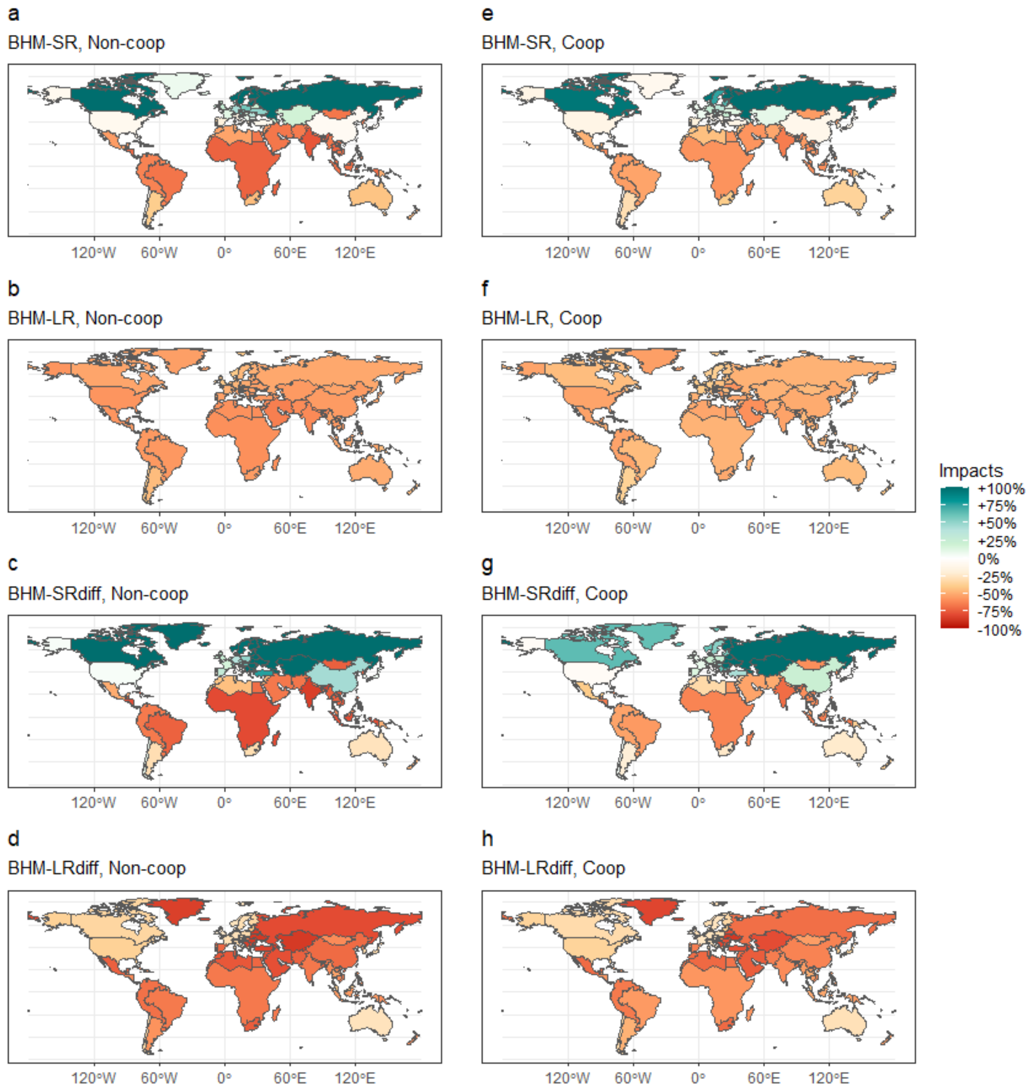
Regions List		
Region	Description	Countries ISO3 numeric Code
Arg	Argentina	ARG
Aus	Australia	AUS
Aut	Austria	AUT
Bel	Belgium	BEL
Bgr	Bulgaria	BGR
Blt	Baltic states	EST, LTU, LVA
Bra	Brazil	BRA
Can	Canada	CAN
Che	Switzerland	CHE
Chl	Chile	CHL
Chn	China	CHN
Cze	Czech Republic	CZE
Deu	Germany	DEU
Dnk	Denmark	DNK
Egy	Egypt	EGY
Esp	Spain	ESP
Fin	Finland	FIN
Fra	France	FRA
FSU	Former Soviet Union	ARM, AZE, BLR, GEO, KAZ, KGZ, MDA, TJK, TKM, UZB
GBR	UK	GBR
Gulf	Gulf Countries	ARE, BHR, IRN, IRQ, KWT, OMN, QAT, SAU, YEM
Grc	Greece	GRC
Hrv	Croatia	HRV
Hun	Hungary	HUN
Idn	Indonesia	IDN
Ind	India	IND
Irl	Ireland	IRL
ita	Italy	ITA
jpn	Japan	JPN
Kor	Korea	KOR
MEast	Middle East	ISR, JOR, SYR, LBN, PSE
Mex	Mexico	MEX
Mys	Malaysia	MYS
Nld	Netherlands	NLD
NAfr	North Africa	ESH, TUN, MAR
NWAfr	North-West Africa	LBY, DZA
Nor	Norway	NOR
Ocean	Pacific Island	CXR, COK, HMD, NFK, NIU, NRU, PCN, TKL, TUV, UMI, WLF, FJI, PNG, FSM, GUM, ASM, TLS, PYF, KIR, MNP, MHL, NCL, PLW, WSM, SLB, TON, VUT, NZL
Pol	Poland	POL

Prt	Portugal	PRT
RCAm	Rest Central America	BES, CUW, SXM, ABW, BHS, BLZ, BRB, CRI, CUB, DMA, DOM, GRD, GTM, HND, HTI, JAM, LCA, NIC, PAN, SLV, TTO, VCT, BMU, SGS, TCA, VGB, VIR, AIA, ATG, BLM, CYM, GLP, KNA, MAF, MSR, MTQ, PRI
REur	Rest Europe	CYP, LUX, MLT, LIE, GRL, ISL, FRO, ALA, AND, GGY, GIB, IMN, JEY, MCO, SJM, SMR, VAT, SPM, BIH, ALB, MKD, MNE, SRB, KSV
Rou	Romania	ROU
RSAm	Rest South America	BOL, COL, ECU, FLK, GUF, GUY, PER, PRY, SUR, URY, VEN
RSAs	Rest South Asia	AFG, BGD, BTN, LKA, MDV, NPL, PAK
RSEAs	Rest South-East Asia	BRN, CCK, KHM, LAO, MMR, PHL, SGP, PRK, HKG, MAC, TWN, MNG
Rus	Russia	RUS
SSAfr	Sub-Saharan Africa	AGO, BEN, BWA, BFA, BDI, CMR, CPV, CAF, TCD, COM, COG, COD, CIV, GNQ, ERI, ETH, GAB, GMB, GHA, GIN, GNB, KEN, LSO, LBR, MDG, MWI, MLI, MRT, MUS, MYT, MOZ, NAM, NER, NGA, REU, RWA, STP, SEN, SYC, SHN, SLE, SOM, SSD, SDN, SWZ, TZA, TGO, UGA, ZMB, ZWE, DJI, IOT, BVT, ATF
Slo	Slovenia	SVN
Svk	Slovakia	SVK
Swe	Sweden	SWE
Tha	Thailand	THA
Tur	Turkey	TUR
Ukr	Ukraine	UKR
USA	USA	USA
Vnm	Vietnam	VNM
Zaf	South Africa	ZAF

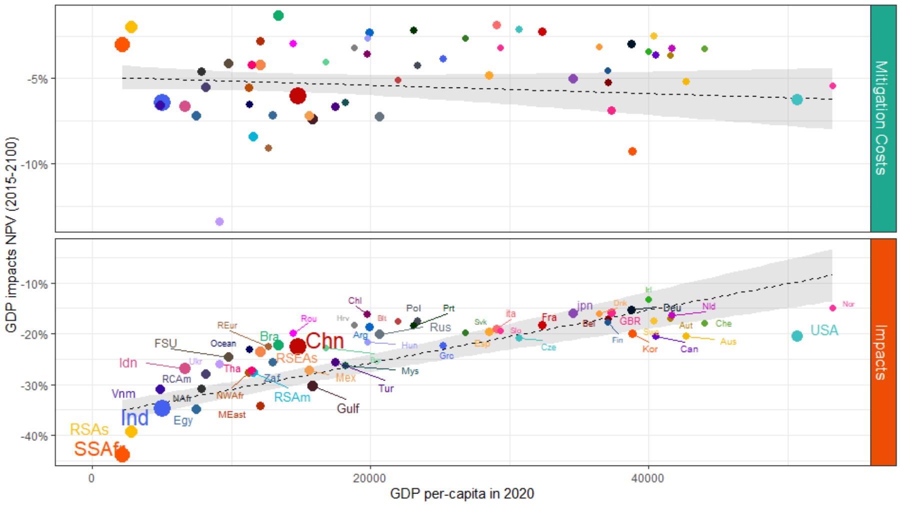
3.B Additional figures



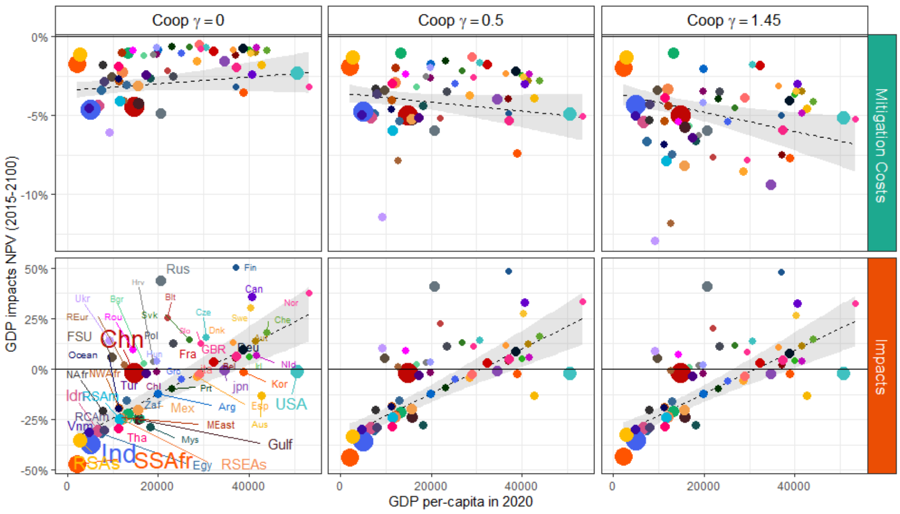
Supplementary Figure 3.6: Mitigation effort map in 2030 and 2050. Values refer to percentage of baseline emissions reduced, under the pathway SSP2 and BHM-SR impact specification. Cooperation uses an intermediate inequality aversion level ($\gamma = 0.5$).



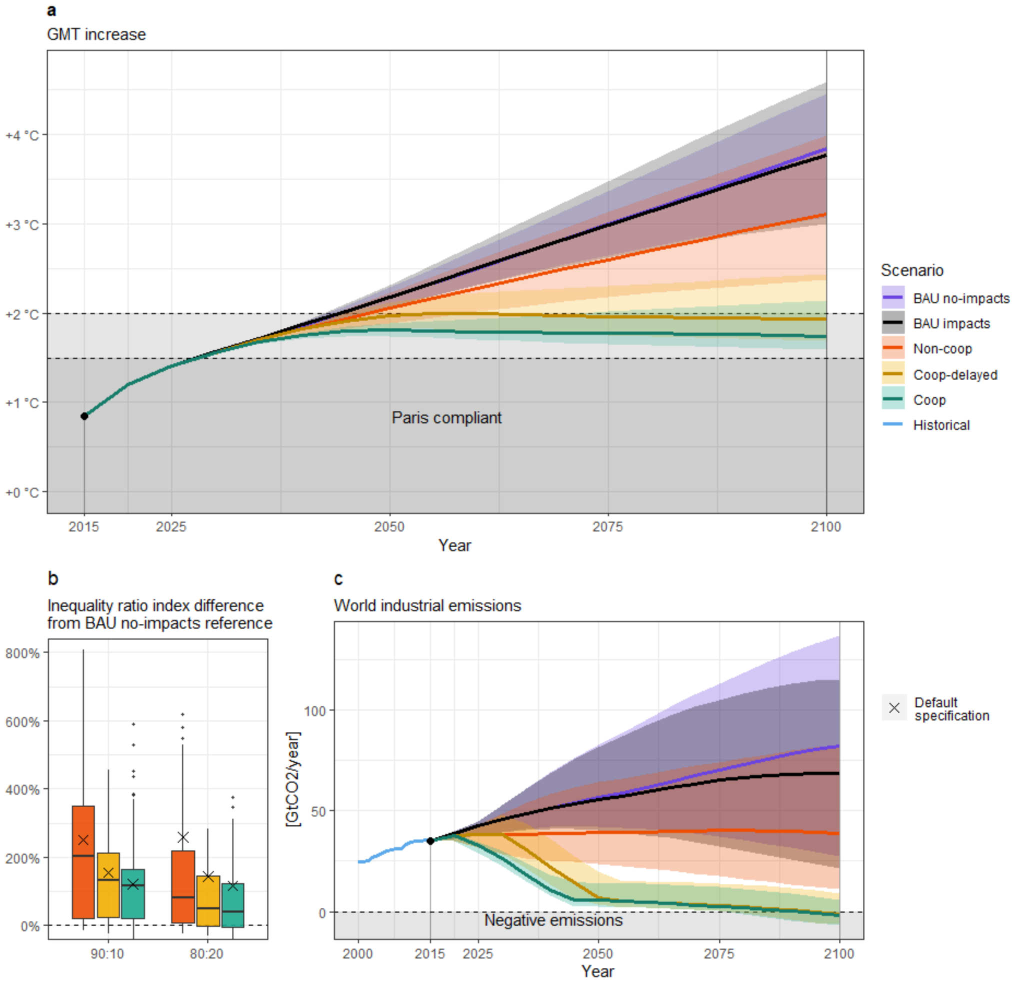
Supplementary Figure 3.7: Climate impacts distribution in 2100. (a-d), Non-cooperative scenario. (e-h), Cooperative scenario with intermediate inequality aversion ($\gamma = 0.5$), socioeconomic pathway SSP2. All four BHM impact-function specifications are shown.



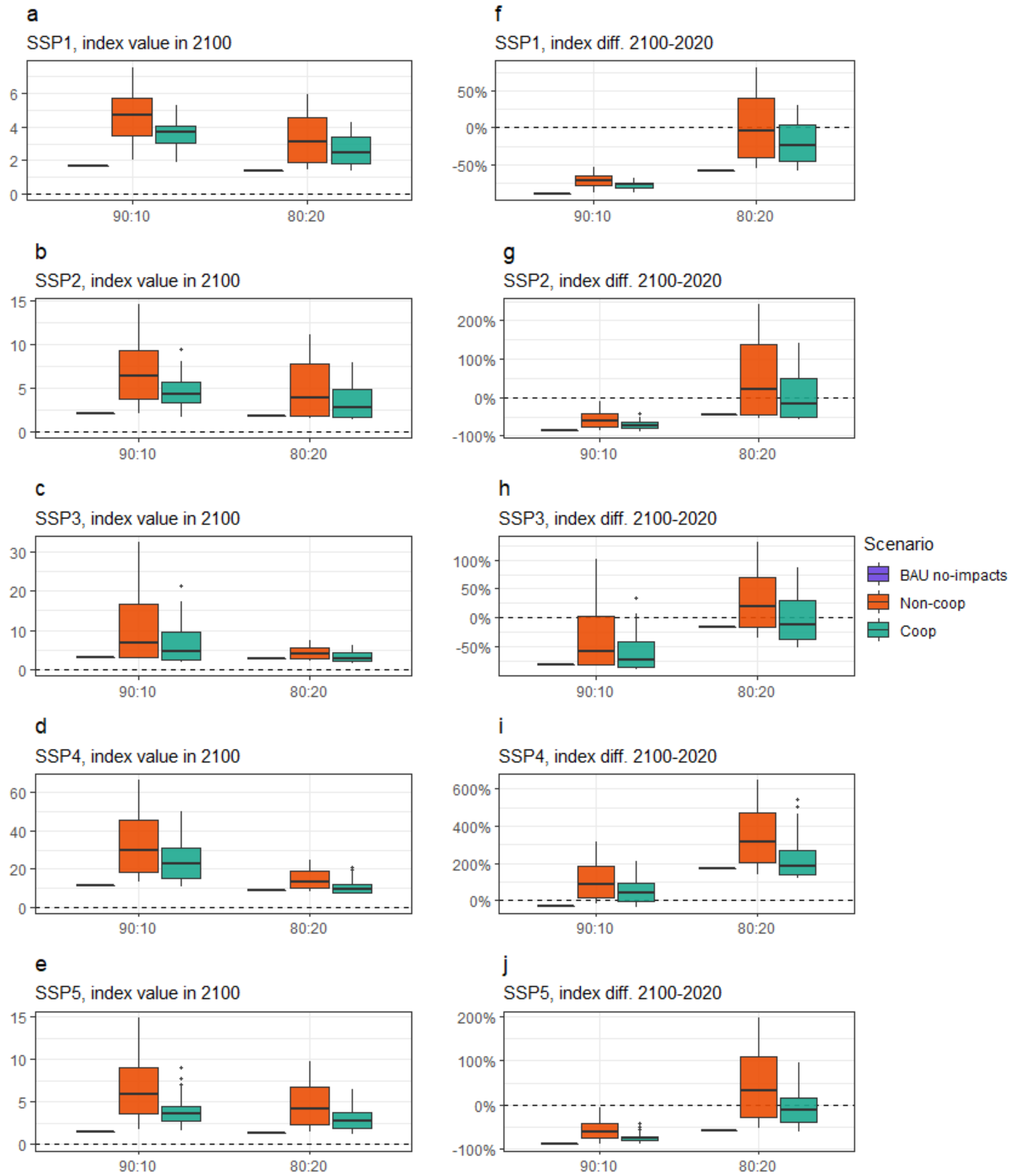
Supplementary Figure 3.8: GDP net present value impacts and costs against 2020 GDP per-capita under BHM-LR impacts. NPV accounts for years 2015-2100, with world-averaged Ramsey yearly discount rate. Reported scenario is cooperative, SSP2, under BHM-LR impact function and intermediate levels for inequality aversion ($\gamma = 0.5$) and utility discount rate ($\rho = 1.5\%$).



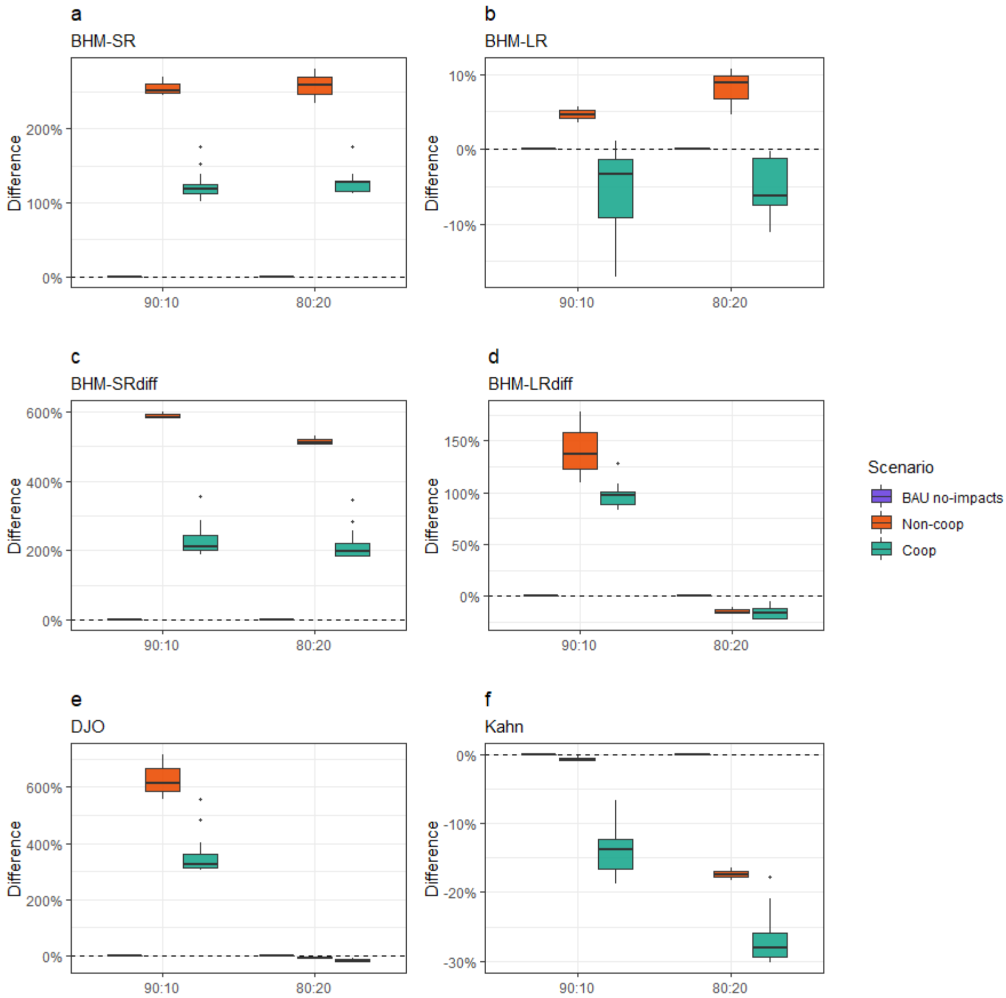
Supplementary Figure 3.9: GDP net present value impacts and costs against 2020 GDP per-capita under alternative inequality aversion values. NPV accounts for years 2015-2100, with world-averaged Ramsey yearly discount rate. Reported scenario is cooperative, SSP2, under BHM-SR impact function, intermediate level for utility discount rate ($\rho = 1.5\%$) and different representative values of inequality aversion γ.



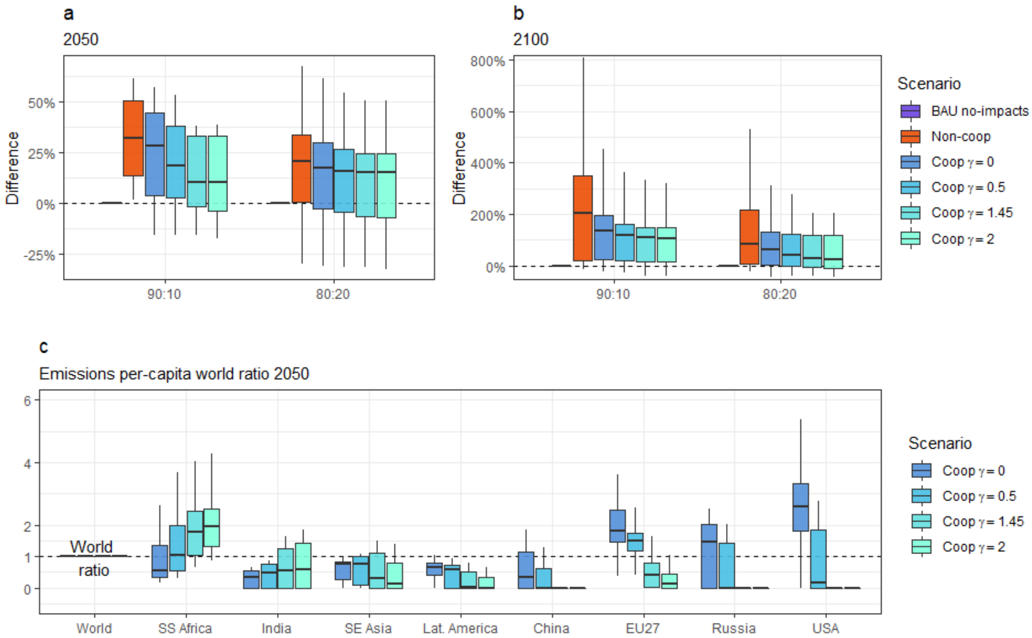
Supplementary Figure 3.10: Optimal outcomes with delayed cooperation. (a), Global Mean Temperature (GMT) increase over time. (b), Inequality index relative difference from BAU-no-impacts for Non-coop, Coop-delayed, and Coop scenarios. (c), World-aggregated CO_2 emissions trends with delayed cooperation. Uncertainty ranges include SSP projection and impact specification. Both Coop and Coop-delayed scenarios are with intermediate inequality aversion ($\gamma = 0.5$). Delayed cooperation starts in 2030.



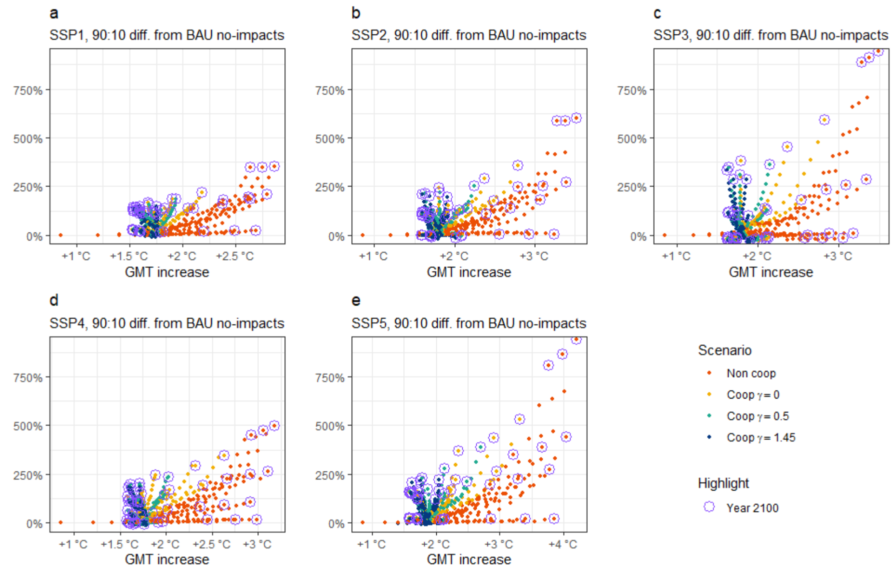
Supplementary Figure 3.11: Inequality index distribution in 2100 for each SSP reference. (a-e), Indexes value distribution. (f-j), Indexes percentage difference from 2020 values: 15.93 (90:10 ratio) and 3.24 (80:20 ratio).



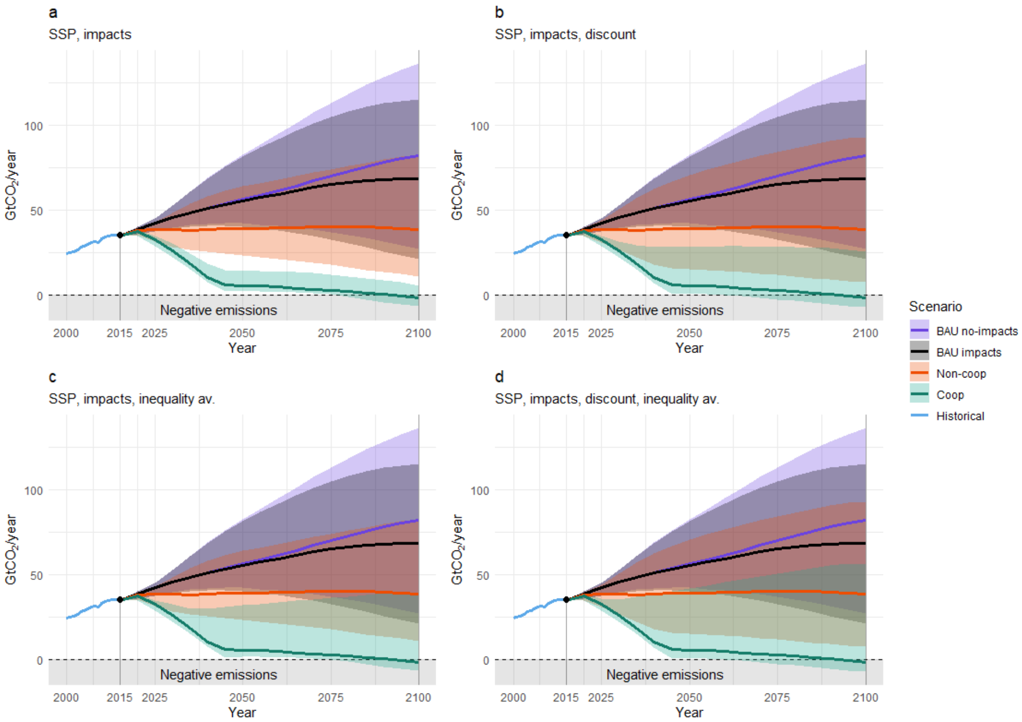
Supplementary Figure 3.12: Inequality index distribution in 2100 for each impact specification. (a-d), BHM main impact specifications. (e), Robustness analysis with DJO impact specification. (f), Robustness analysis with Kahn impact specification. All values refer to percentage difference from BAU-no-impact references.



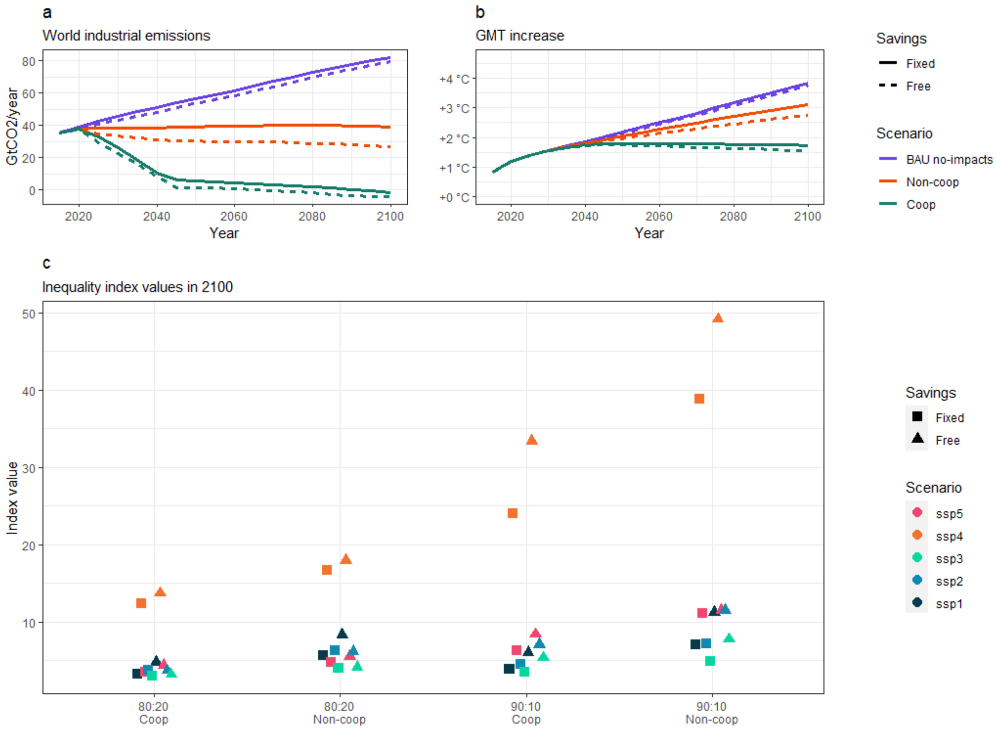
Supplementary Figure 3.13: Inequality aversion effect on inequality and emissions. (a), Inequality index relative difference from BAU-no-impacts for Non-coop and Coop under increasing inequality aversion in 2050. (b), Inequality index relative difference from BAU-no-impacts for Non-coop and Coop under increasing inequality aversion in 2100. (c), Ratio between main regions and world emissions per-capita distribution under Coop at increasing inequality aversion. They show the aggregated level from finer geographical-resolution results.



Supplementary Figure 3.14: Ratio 90:10 inequality index over GMT increase, for each SSP scenario. The y-axis shows percentage difference from BAU-no-impacts levels. Time dimension (2015-2100) is hidden in data, but 2100 levels are highlighted. Colors show also different levels of inequality aversion.



Supplementary Figure 3.15: Optimal world-aggregated model emissions with different uncertainty ranges. (a), Uncertainty ranges include SSP baselines and impact definitions (as in Figure 1a). (b), Uncertainty ranges include SSP baselines, impact definitions and utility discount rate. **c,** Uncertainty ranges include SSP baselines, impact definitions and inequality aversion. **d,** Uncertainty ranges include all factors: SSP baselines, impact definitions, utility discount rate and inequality aversion.



Supplementary Figure 3.16: Comparison between fixed and endogenous savings rate solutions. (a-b), World emissions and GMT increase for SSP2 baseline and main cooperation options. (c), Inequality indexes comparison across all SSP scenarios both for cooperative and non-cooperative solutions.

Chapter

4

An Agent-based negotiating framework for international climate agreements[1]

4.1 Abstract

International Environmental Agreements on greenhouse gases emissions reductions demonstrated to be extremely hard to achieve and uphold. Several studies have been searching for self-enforcing strategies to enlarge cooperation and enforce agreement stability, usually supported by models grounded on game theory. However, the public-good nature of climate change makes it an exceptionally complex problem with many time-varying international issues which are hard to be all accounted for in any game-theoretical framework. Here we propose an agent-based negotiation framework as a novel approach to investigate the complex and distributed decision-making processes of international negotiation on greenhouse gases regulation. The simulation model follows a bottom-up approach, starting from a modelled behaviour for each region-representative negotiator. Agents generate and update their own emissions mitigation proposals following private multi-objective evaluations over potential upcoming scenarios (informed by the RICE50+ Integrated Assessment model regional benefit-cost projections), reactions to other players' proposals, and private negotiating strategies.

4.2 Introduction

International negotiation and cooperation on climate change represent one of the most critical global public-good problems of present times. International Environmental Agreements (IEAs) have demonstrated to be extremely hard to achieve and resist the curse of free-riding over time. Even after the Paris Agreement, the most important milestone reached by the Conference Of Parties (COP) in recent years, the risk of withdrawals may curse the cooperation on mitigation actions. The possibility of sudden turnarounds, like those set by the U.S. after flipping results in political elections, could prevent other countries from increasing their voluntary participation (Keohane and Victor, 2016). on the other hand, a rising commitment is advocated by several studies (e.g., see

[1]This chapter is drawn from an early draft of the paper "An Agent-based negotiating framework for international climate agreements" by P. Gazzotti, A. Castelletti, M. Tavoni. At the moment of writing it is targeting *Environmental science and policy* journal.

Höhne et al., 2017; Rogelj et al., 2016) as imperative to meet the ambitious goal of limiting global temperature increase *well below 2°C, preferably to 1.5°C compared to pre-industrial levels* by the end of this century (UNFCCC, 2015).

Several studies have provided modelling solutions in search for insights and strategies to incentivize international cooperation. An important research stream uses Integrated Assessment Models (IAM) to estimate scenarios of coalitions formation and their inner stability performance (e.g., see Bosetti, Carraro, De Cian et al., 2013; Carraro and Siniscalco, 1992; Lessmann et al., 2015; Nordhaus, 2015). They all mainly use benefit-cost policy-optimizing IAMs with some regional detail and interaction rules of fundamental game-theory solutions: the cooperative social-welfare maximization and the non-cooperative Nash equilibrium (e.g., see Bosetti, Carraro, Galeotti et al., 2006). Other contributions, on the contrary, follow more specific game-theoretical methodologies to address problems of IEAs stability (e.g., see Battaglini and Harstad, 2016; Bayramoglu, Finus and Jacques, 2018; Biancardi and Villani, 2014), structural incentives for cooperation (e.g., see Cole, 2011; Schwerhoff et al., 2018) or optimal transfers to adjust asymmetries (e.g., see McGinty, 2007).

Game theory modelling, however, despite being a powerful tool and rigorous investigation technique, exhibits some significant limitations within the framed context of global environmental regulation. First of all, game-theory-based models are often affected by an exponential complexity growth that follows the increase of the decision arguments or decision-making entities considered. In fact, most of the literature methodological settings rarely go beyond simplified games among a handful of individuals and very circumscribed disputes (cf. McGinty, 2020 and references within).
Secondly, the math framework itself, once defined, is usually quite laborious to modify and update. Hence, it may lack the proper flexibility to adequately follow the very dynamic context of international negotiations, where positions, perspectives, and interaction rules may rapidly and drastically change, with considerable effects on the potential outcomes (Dimitrov, 2016).
Last but not least, game theory models frequently suppose perfect knowledge and complete rationality among the involved decision-makers (i.e., discussion of economic payoffs only). These assumptions do not necessarily hold in the international climate change debate (Finus, 2008).

Here we propose a new exploratory approach to support the investigation of IEAs formation and cooperation incentives for global greenhouse gases emissions regulation. We define an Agent-Based Modeling (ABM) framework that aims at recreating both international discussion dynamics and individual decision-making processes. It comprises several autonomous agents who can interact, propose and carry out intentional mitigative actions. They share the same environment and are subjected to climate feedbacks and some formalized communication rules. This framework is intended to support and complement the consolidated literature modelling solutions, providing a different perspective and a flexible tool that enables the investigation of a broader range of scenarios. ABM has already been appreciated as a very effective technique when addressing complex environmental problems with multiple conflicting stakeholders (e.g., see Amigoni et al., 2016; Athanasiadis, 2005). Bonabeau (2002) identifies three substantial benefits of ABM over other modeling techniques when simulating

human systems.
First, ABM captures *emergent phenomena* that result from the interactions of individual entities and cannot be assessed from the analysis of the system's parts. Significant emergent phenomena generate when individual behaviour is nonlinear (e.g., characterized by thresholds and discontinuities), when it exhibits memory, path-dependence, or includes learning and adaptation to other individuals.
Secondly, they provide the significant advantage of their ease of implementation, as they allow the modelling of an exceptionally complex system starting from its building blocks (see also Wooldridge, 2009). They offer a natural and powerful descriptive approach for describing and simulating a system composed of entities with complex behaviour.
Last, ABM is exceptionally flexible. For example, it allows adding more agents, varying their degree of rationality, ability to learn and evolve, and primary rules of interactions. Modellers can easily change levels of description and aggregation without being affected by an exponential complexity growth as in more conventional game-theory systems.

Nonetheless, to the best of our knowledge, ABM usage has been quite limited in the framed context of greenhouse gases regulation so far. Notable contributions are only Geisendorf (2018), where agents contribute to balance different perspectives inside an IAM, and Earnest (2008), where author modelled a three-choices international coordination problem among negotiating states.

In the following sections, we provide a general description of the main assumptions and structure of the framework. Then, we describe the details of agent components, decision processes and interaction rules. We show a first calibration attempt of the model, based on the benefit-cost data projections coming from a RICE50+, a highly-regionalized optimizing IAM. We completed the description with some representative experiments that show how the model behaves in the given scenarios. We conclude with a general discussion on the presented approach depicting future applications and research improvement directions.

4.3 The model

General framework

The model comprises a recurring negotiation schema that takes place every *time-step* t (a time measure accounting for 5-years each). Diplomat agents i virtually gather to discuss a shared objective (hereafter *agreement* $\mathcal{A}(t)$) to limit personal greenhouse gas emissions (hereafter also called *emissions budget* $\mathcal{B}_i$), on a voluntary base, within a specific time in future t_{neg}. Once an agreement is reached, all regional economies evolve synchronously by one time-step: $t \rightarrow t+1$. During this phase, each agent decides whether to comply with its agreed commitment (i.e., to apply mitigation policies in line with announced emissions reductions) or not. At the end of this evolution phase, agents gather again to re-discuss their commitments for a future period of equal length. That includes a potential redefinition of the previous agreement for its remaining valid time (e.g., 15 years), plus a new commitment for the additional time-step (e.g., subsequent 5-year period). This process definition allows the

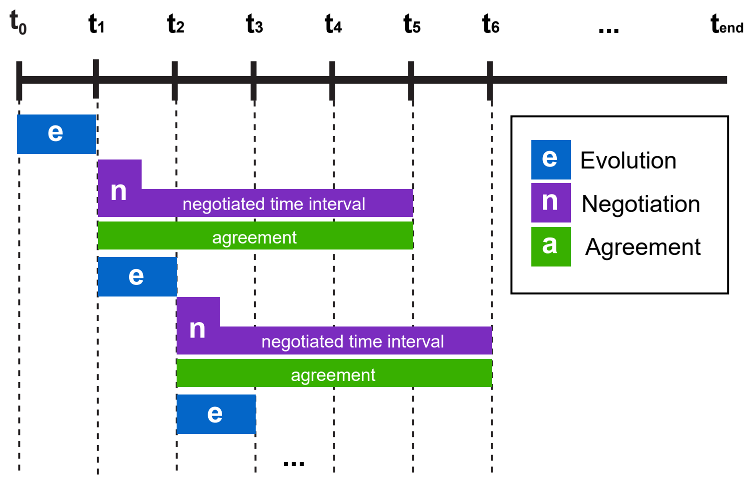


Figure 4.1: General model schema; a continuous sequence of evolution/negotiation alternation.

modeller to include also abrupt changes in mitigation ambition for specific agents (e.g., a consequence of sharp governor shift after flipping elections).

The alternating evolution-negotiation sequence starts in 2015 (with 2015-2020 evolution pre-determined on historical data) and repeats up to a specific time boundary (e.g., end of the current century). The general recurring schema described so far is graphically synthesized in Figure 4.1.

Agents

Agents are self-standing and autonomous entities that operate their choices and actions inside a shared environment, following a few general rules. They may represent geographical regions, political coalitions, interest-based clubs, up to single sovereign states. Each agent is structured into different components that are shown in Figure 4.2. All the components are tightly interconnected, yet each serves a specific role.

The *diplomat* (1) component includes methods and interfaces to communicate with other agents and exchange information in negotiations. It represents the political facade of the agent.

The *economy* (2) component includes a stylized representation of regional economic growth and evolution. It comprises a simplified set of equations that follow the renowned Nordhaus' DICE/RICE IAMs structure (Nordhaus, 2008;

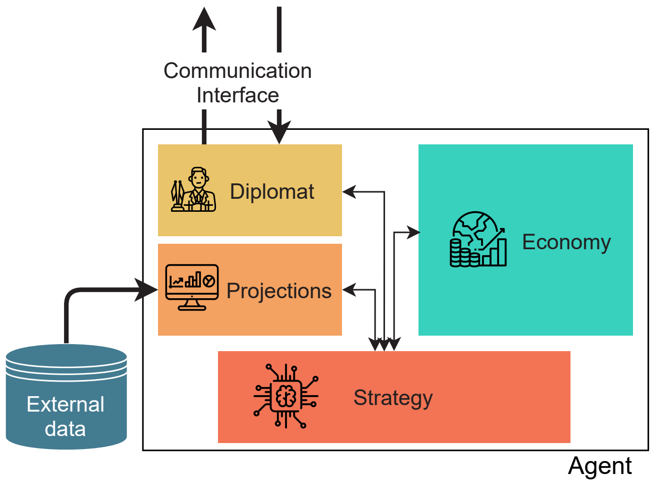


Figure 4.2: Schema of agents structure and constituting components.

Nordhaus and Yang, 1996). In the presented setup, however, economies data and parameters account for the geographical subdivision and the calibration process adopted in another regional IAM called RICE50+ (Gazzotti, 2021). Consequently, the *economy* component can execute five alternative and coherent future scenarios, the Shared Socioeconomic Pathways (SSP) (O'Neill et al., 2014; Riahi et al., 2017), and several alternative impact functions as well. It inherits also RICE50+ assumptions on maximum mitigation increase and decrease rate per each time step, and its regional abatement cost curves. Hence, at every evolution step, the equations of this component determine the agent's GDP production, capital accumulation, consumption, emissions rate, and mitigation costs. Climate change impacts also apply, as a consequence of aggregated emissions rate from all the agents, and related Global Mean Temperature (GMT) increase. Appendix 4.B briefly summarizes all the main related equations. Refer to Gazzotti (2021) for a more exhaustive and detailed description of these.
Each agent can also use its *economy* component to make projections on its own potential growth and evolution, by providing a hypothetic mitigation profile and an assumption on future GMT levels as input.

Then comes the *projections* (3) component, which gives access to external data sources. In this way informative projections and assessments, both at the local and global scale, are provided to the agent, supporting with data its decision-making process. In the presented configuration, this component is connected to a dataset that contains several RICE50+ benefit-cost optimal assessments, performed under different scenarios assumptions, used and described also in Gazzotti et al. (2021).

Last, the *strategy* (4) component represents the core decision-making unit. It combines data from the *projections* component with negotiation information from the *diplomat*, and performs some scenario evaluation using the *economy* as well. It provides, as output, decisions on agent negotiation proposals and mitigation policies to eventually apply.

Climate

Detached from the main negotiation infrastructure, the model includes also a simplified climate module. It evaluates the climatic consequences, for each evolution time step, once that all the agents have decided their mitigation policies and therefore their aggregated emissions rate. Hence, this module evaluates the cumulative CO2 concentration in the atmosphere and defines the consequences in temperature forcing, GMT increase and oceans mean temperature increase. This information is passed back to the agents so that they can assess consequences such as climate change impacts on their local economies. In the presented setup, we opted for the same climate-regulating equations as in the RICE50+ climatic module, for the sake of simplicity and general consistency.

Negotiation framework

During the negotiation phase, agents gather to discuss their voluntary *emissions budget* for a specific future period t_{neg}. The negotiation process is coordinated by a *mediator*, which collects diplomats' proposals and evaluates whether an agreement has been reached or not. Despite not being strictly essential, the mediator helps to limit the number of messages exchanged by agents and synchronize their decisions (evaluated in parallel).

Figure 4.3 shows a representative schema for the negotiation phase. The process is started by the mediator which asks all diplomats (i) to make their evaluations and get ready to submit the first proposal $\mathcal{P}_i(r = 1)$. Once all diplomats have sent their proposals to the mediator, it evaluates the aggregated result. If the final condition is not reached, the mediator sends round information to all the diplomats, asking them to update their proposals. Agents receive round information (including others' proposals) and evaluate next-round proposals according to their private strategy: $\mathcal{P}_i(r + 1) = \mathbf{S}_i\big(\mathcal{P}_i(r), \mathcal{P}_j(r), ...\big)$. The sequence is repeated, round after round, until the final condition is met. Hence, the mediator declares the agreement, shares final information with all the diplomats (which formally ratify it), and closes the negotiation. The algorithm steps for both the diplomats and the mediator are reported as pseudocode in Appendix 4.A.

Proposals and negotiation rules

With the general framework described so far, we have to set some rules to guarantee negotiation convergence and termination. The presented setting aims to balance the realism of the diplomats' debate with the necessity to provide a well-scalable computational complexity at the increasing number of participant agents.

The proposals $\mathcal{P}_i(r)$, exchanged at each negotiation round r, by agent i, are defined by the following tuple:

$$\mathcal{P}_i(r) = \langle \mathcal{B}_i(r), \text{final}_i(r) \rangle. \tag{4.1}$$

Term $\mathcal{B}_i(r)$ provides the actual value of emissions budget each agent i proposes for itself at round r. The boolean flag *final*, on the other hand,

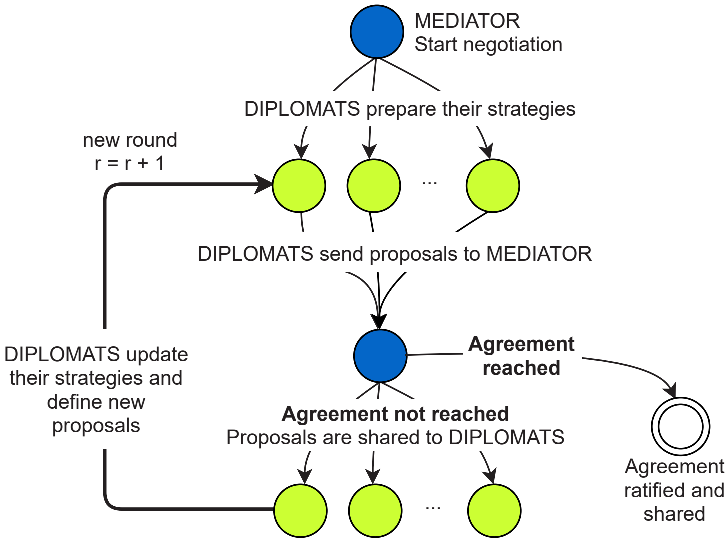


Figure 4.3: Negotiation schema as sequence of rounds with diplomats and mediator interactions.

indicates whether the agent has some residual willingness of changing its proposal (final $=$ *false*) or has reached a non-negotiable final state (final $=$ *true*).

Furthermore, some general rules apply to the negotiation process. They are common knowledge among all the participants. The mediator, after collecting diplomats' proposals at each round, verifies that all the rules are constantly met.

Negotiation rule 1. *The negotiation terminates when at least all-but-one diplomats declare themselves in* final *state. Proposals values announced in the final round constitute the* agreement *solution.*

Negotiation rule 2. *Once a diplomat declares himself in* final *state, it will not be anymore allowed to update its proposal.*

Negotiation rule 3. *Every subsequent round proposal must be strictly improving the previous one (i.e., announcing a lower amount for the diplomat's emissions budget). If a diplomat does not improve his proposal he is consequently considered as in* final *state.*

Strategy

In this section, we describe the main dynamics that regulate agents decisions and behaviour. Following functions and their parameters are agent-specific and kept undisclosed as private information.

First proposal

The process for choosing the first proposal differs according to whether the agent is participating in the first negotiation of the series or not. In the former case, agents start by proposing their most convenient option given the public-good nature of climate change: the free-riding, no-mitigation-equivalent proposal. In the latter case, however, there could be a previously negotiated agreement still holding for some future time steps (e.g., as in the sequence shown in Figure 4.1). Here agents, always following a free-riding approach, start the negotiation proposing the equivalent of a reduced commitment (i.e., the agreement discounted by a private factor δ_i), integrated by the lowest mitigation option for the additional time step. As a consequence, this behaviour reopens the discussion at every subsequent negotiation step.

Proposal update

Agents update their proposal following an egocentric concession protocol (Endriss, 2006). Starting from the ideal optimum (a free-riding, low-commitment proposal), they progressively concede, updating their proposal according to the following rule:

$$\mathcal{B}_i(r+1) = \mathcal{B}_i(r) - \alpha_i \cdot \max\left(\mathcal{B}_i(r) - \overline{\mathcal{B}}_{i,\mathrm{maxwill}}(r), \quad 0\right). \tag{4.2}$$

As a result, at every non-final round emissions budget is reduced by a small fraction, until $\mathcal{B}_i(r) \leq \overline{\mathcal{B}}_{i,\mathrm{maxwill}}(r)$. When that applies, agent enters the final state and stops conceding. Here, $\overline{\mathcal{B}}_{i,\mathrm{maxwill}}(r)$ represents the agent's critical threshold of *maximum concession willingness*; $\alpha_i \in (0, 1]$ represents a general concession speed factor. While α_i is fixed along the entire negotiation phase, the threshold $\overline{\mathcal{B}}_{i,\mathrm{maxwill}}(r)$ can vary (for example, reflecting an agent's reaction to others' proposals).
In particular, this term is defined as follows:

$$\overline{\mathcal{B}}_{i,\mathrm{maxwill}}(r) = \mathcal{B}_{i,\mathrm{basewill}} + \psi_i(r). \tag{4.3}$$

Here, $\mathcal{B}_{i,\mathrm{basewill}}$ represents a base-reference that we identify with the rationale solution for agent i in public-good strategic games. That is a Nash equilibrium solution in a non-cooperative setup. Component $\psi_i(r)$, on the other hand, represents the aggregate additional *decision-forcing* that pushes the agent's willingness towards different (in principle both higher and lower) solutions. According to this definition, inside the $\psi(r)$ component would reside all those decision factors and multi-objective evaluations that could push an agent to a cooperative commitment rather than a pure-selfish one.

Parameters calibration

To calibrate the proposed framework we started from optimal non-cooperative estimates of IAMs with sufficient regional granularity. Here we adopted benefit-cost solutions from the RICE50+ model, which are provided by the agents' *projections* component. In principle, each agent can set its own base willingness level $\mathcal{B}_{i,\mathrm{basewill}}$ by selecting a different experiment or scenario reference sources. For example, distinct agents could be accounting for diverse assumptions on critical normative parameters (i.e., inequality aversion or intergenerational discount rate Azar and Sterner, 1996; Cline, 1992; Stern, 2006) or give more credit to different impact functions according to their risk-aversion. For the presented purpose, however, we considered all agents referring to the same projection: SSP2 baseline with Burke-SR empirically-estimated impact function.

On the other hand, to estimate agents' additional decision-forcing ψ_i and, consequently, their maximum concession willingness $\overline{\mathcal{B}}_{i,\text{maxwill}}(r)$, several concurrent dimensions and multiobjective tradeoffs can be accounted for. They could include, for example, air pollution co-benefits, interests in low-carbon technologies development, geopolitical incentives for energy independence, or inequality aversion ethic principles. As a starting point, here we considered current NDCs and recent carbon-neutrality goal announcements as a useful proxy to set agents maximum concession willingness.

We close this descriptive section of the model with an important caveat. Despite the high expressivity and modelling power provided by the presented framework, it is important to remark how it cannot rely on proper validation due to the lack of sufficient disclosed data and time-series from real COP negotiations. Future applications, therefore, must necessarily pass through sensitivity-analysis validation for all the main parameters of the strategy function.

4.4 Illustrative results

Model setup and scenarios

For illustrative purposes, we set up the negotiating framework defining 57 independent agents, which follow the same regional subdivision of coupled RICE50+ model (see also Figure 4.7 in Appendix 4.C section). This choice proves the scalability of the presented modelling solution, which can bear the interactions of a large number of independent decision-makers. Individual strategies, then, are set as follows. Concession speed α_i is set equal among all the agents and for every negotiation phase, to better isolate the primary effect of the decision-forcing component. Then, we differentiate three alternative settings.

No-forcing Here agents' strategies are regulated by their base willingness $\mathcal{B}_{i,\text{basewill}}$ only. The additional forcing component is null: $\psi_i(r) = 0$. Hence, we expect agents to follow and pursue proposals in line with optimal policy projections under noncooperative assumptions.

NDCs In this configuration agents' strategies are affected by an additional forcing ψ_i, calibrated on NDCs commitments. This is obtained by estimating, for each region, the emissions-budget in line with NDCs targets for year 2030 (as assessed by Hof et al., 2017 and Elzen et al., 2016), and evaluating the difference with RICE50+ non-cooperative projections equivalent. This difference is finally normalized upon the range of maximum and minimum technical feasibility extremes for the emissions-budget. Equations 4.4 and 4.5 summarize the described process:

$$\xi_{i,\text{NDCs}} = \frac{\mathcal{B}_{i,\text{NDCs}} - \mathcal{B}_{i,\text{noncoop},2030}}{\mathcal{B}_{i,\text{techmax},2030} - \mathcal{B}_{i,\text{techmin},2030}}, \tag{4.4}$$

$$\psi_{i,\text{NDCs}}(r) = \xi_{i,\text{NDCs}} \cdot \big(\mathcal{B}_{i,\text{techmax}}(t) - \mathcal{B}_{i,\text{techmin}}(t)\big). \tag{4.5}$$

The resulting additional forcing then evenly applies in all the negotiation phases. Note, in conclusion, also the importance of the resulting sign: when ψ_i is negative (i.e., NDCs more ambitious than the non-cooperative solution) its contribution is driving the agent towards lower budget proposals (and therefore higher mitigation commitments); the other way around when ψ_i is positive.
Here we expect most of the policy proposals still quantitatively close to non-cooperative optimal levels yet with some noticeable differences for specific countries (cf., India in NDCs and non-cooperative projections comparison in Gazzotti et al., 2021).

NDCs and Carbon Neutrality In this last configuration agents' strategies have an additional forcing ψ_i calibrated upon carbon-neutrality declarations, for those regions which have publicly announced the intention so far. They include the U.S., European-Union members, Japan, South Korea (all targeting year 2050), and China (targeting year 2060). The calibration process is analogous to the NDCs case, with $\xi_{i,\text{CNeutral}}$ and $\psi_{i,\text{CNeutral}}(r)$ now defined as:

$$\xi_{i,\text{CNeutral}} = \frac{\mathcal{B}_{i,\text{CNeutral}}(\hat{t}) - \mathcal{B}_{i,\text{noncoop}}(\hat{t})}{\mathcal{B}_{i,\text{techmax}}(\hat{t}) - \mathcal{B}_{i,\text{techmin}}(\hat{t})}, \tag{4.6}$$

$$\psi_{i,\text{CNeutral}}(r) = \xi_{i,\text{CNeutral}} \cdot \big(\mathcal{B}_{i,\text{techmax}}(t) - \mathcal{B}_{i,\text{techmin}}(t)\big), \tag{4.7}$$

with $(\hat{t})$ as region i target-year for carbon neutrality. For those regions which haven't declared any carbon neutrality goal, NDCs forcing component is kept, evaluated as described previously.
Here we expect a considerable higher ambition in policy proposals for those agents aiming at reaching carbon neutrality. However, we still don't expect global regulation to attain steep decarbonization since a significant amount of countries still endows low-ambitious NDCs proposals within the negotiation game.

Effects on single negotiation

Figure 4.4 shows, for each of the three scenarios defined, the continuous sequence of emissions-budget values proposed by each agent during the first-negotiation rounds. Budgets $\mathcal{B}_i(r)$ values are normalized upon each agent's maximum-minimum feasibility range (shown on the y-axis, expressed in percentage points) for a better comparison. The x-axis shows the progression of negotiation rounds. Hence, the lower the curve goes, the lower the emissions budget proposed by the diplomat agent becomes (i.e., higher ambition in voluntary decarbonization). Informative labels help to locate the position of the curves for the top-20 baseline emitters.
The figure depicts an evident shift towards lower budgets when more ambitious decision forcings are introduced. In fact, while panel (a) simply matches the non-cooperative efforts as projected by the RICE50+ model in 2020 (see Gazzotti et al., 2021), panel(b) and (c) show some modest and significant overall improvements respectively (i.e., lowering) in the agents' maximum willingness threshold. The final agreement reached will therefore include higher voluntary participation, as a direct consequence of this. We notice also how negotiation rounds needed to reach convergence more than double from panel (a) to panel (c) scenario.

We complete the single-negotiation analysis with Figure 4.5, which shows the same curves now for six representative agents. India, in panel (a), and Gulf countries, in panel (b), are two cases where the agent proposes higher emissions-budgets than its rationale non-cooperative solution. Here NDCs-calibrated ψ_i is, therefore, a positive-sign factor that pushes the agent towards lower mitigation (i.e., higher emissions budget) proposals. China, The U.S. and Germany (selected as a representative case for all the EU members), from panel (c) to panel (e), show another significant type of behaviour. Here, while NDCs-calibrated decision forces lead to solutions quite close to the non-cooperative equivalent, recent carbon-neutrality target declarations reveal a remarkably more resolute interest and willingness for cooperation. Last, in panel (f), Russia provides the example of an agent who has neither perceived convenience nor actual intention (according to the presented calibration) to propose any voluntary emissions reduction. Agents of this kind immediately declare themselves in *final state* during the first negotiation rounds and are adverse to any concession.

Effects on repeated negotiations

Figure 4.6 shows total global emissions over time, therefore accounting for a sequence of several negotiations. *BAU* line displays the reference emissions profile for the unmitigated SSP2 evolution. Model emissions progressively detach from this curve over time, keeping closer to RICE50+ non-cooperative solution equivalent. This is largely expected, being this latter curve agents' base reference and given that, in the current setup, agents effectively mitigate what they promise in each negotiation agreement. On the other hand, we notice that *No-forcing* scenario emissions don't perfectly match the model RICE50+ projection. This is due to the greedy process used to translate the emissions budget into an equivalent sequence of mitigations, which may generate slightly different trajectories than the optimal benefit-cost ones.

Having a *NDCs*-forcing scenario very close to the *No-forcing* one is not surprising either. In fact, to those countries that increase their policy commitment, there counterbalance other ones decreasing their proposals. The scenario that combines *NDCs and Carbon Neutrality*, instead, is showing a noticeable lower emissions profile during the first time-steps. This is due to the additional decision-forcing component which drives those countries who have publicly declared it. However, we also see that, in the long run, the curve converges to similar levels as the other ones. This is understandable considering that carbon-neutrality declarations come from developed countries, for whom the baseline scenario already accounts for significant decarbonization of the economic sectors. Therefore, long-run emissions are essentially due to emergent countries, not driven by any carbon-neutrality forcing yet.

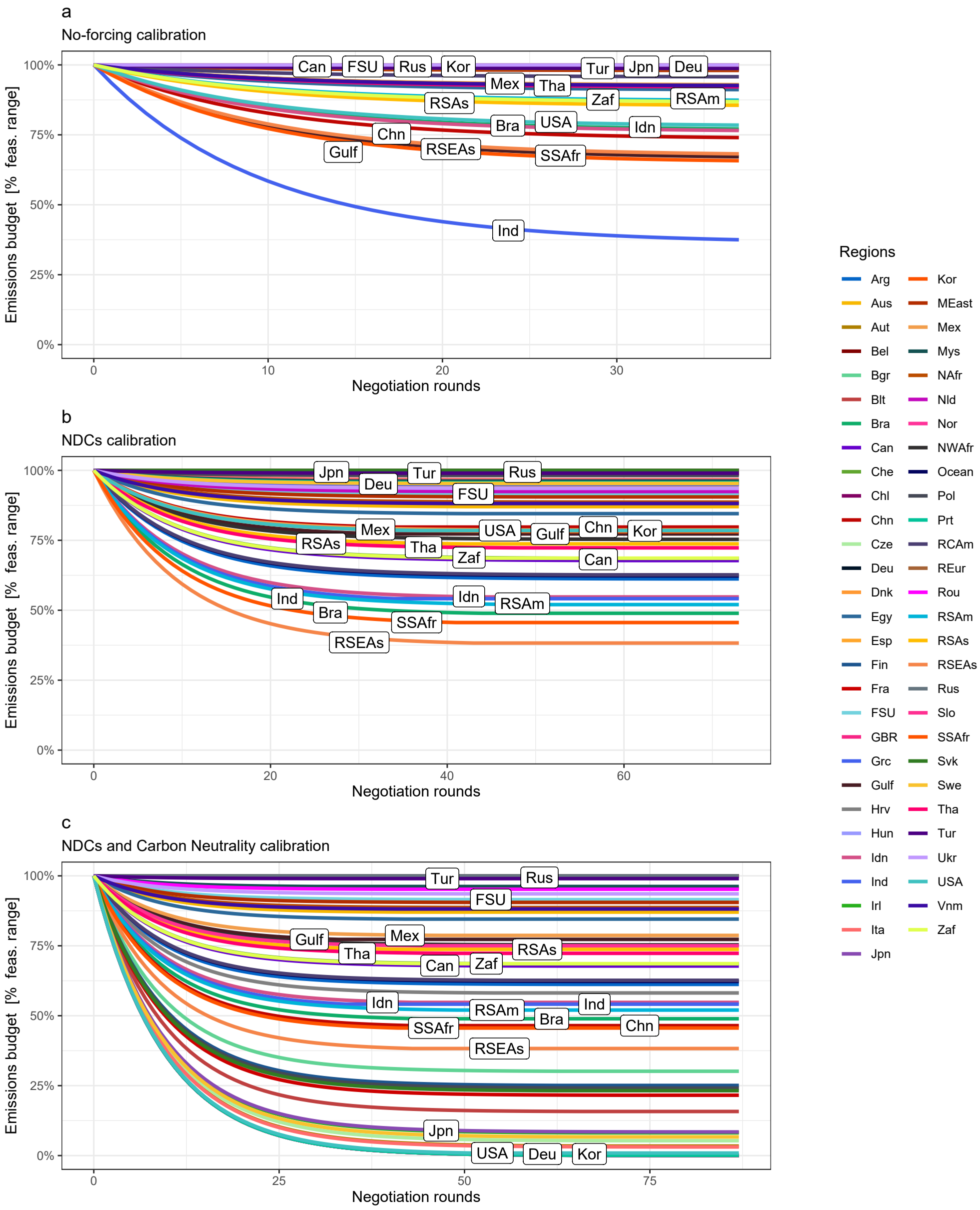


Figure 4.4: Sequence of emissions-budget values proposed by each agent during the first negotiation. Budgets $\mathcal{B}_i(r)$ are normalized upon each agent's feasibility range (y-axis, expressed in percentage points). The x-axis indicates the evolution of negotiation rounds. Labels are added to locate the curve position for the top-20 baseline emitters.

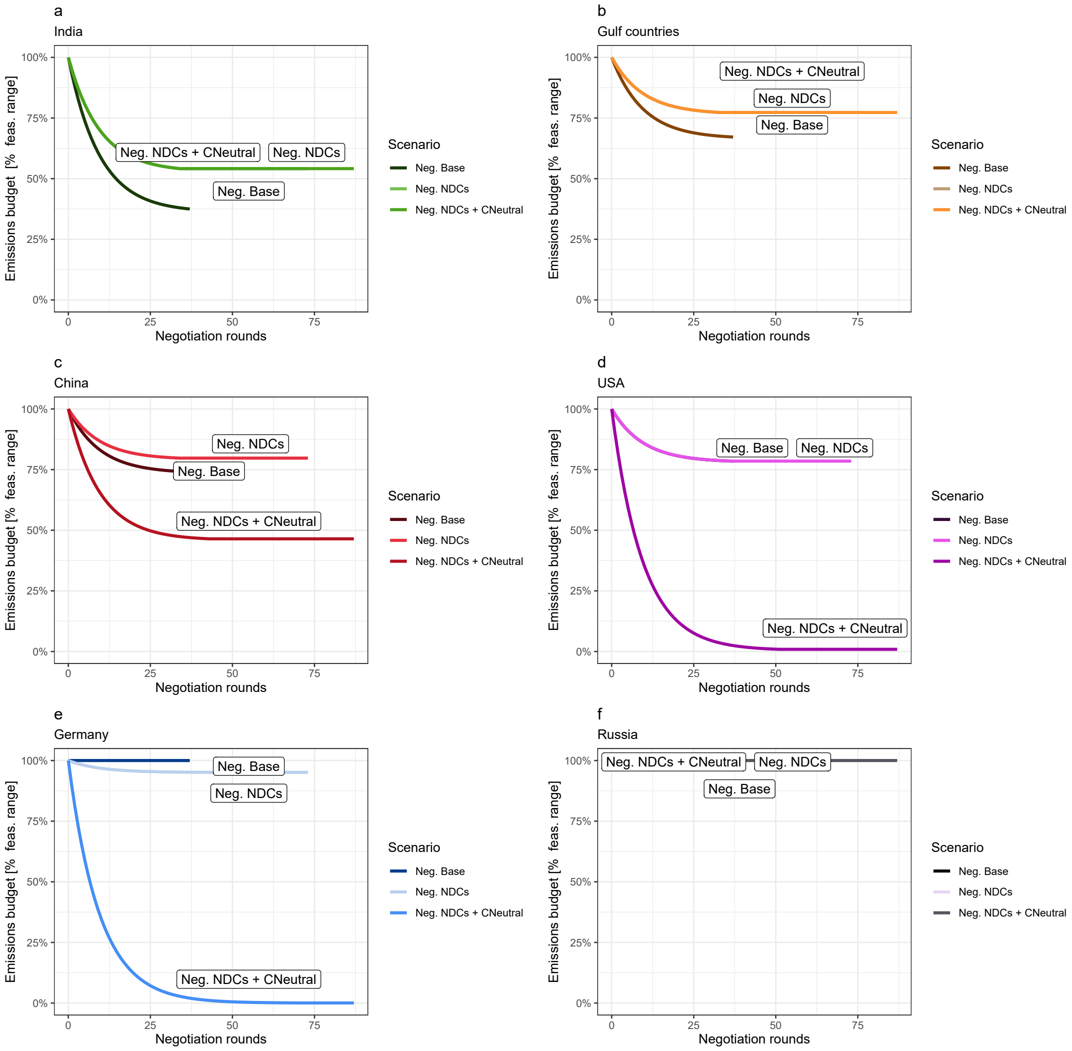


Figure 4.5: Sequence of emissions-budget values (normalized upon each agent's feasibility range and expressed in percentage points) proposed by selected representative agents during the first negotiation for the three scenarios defined.

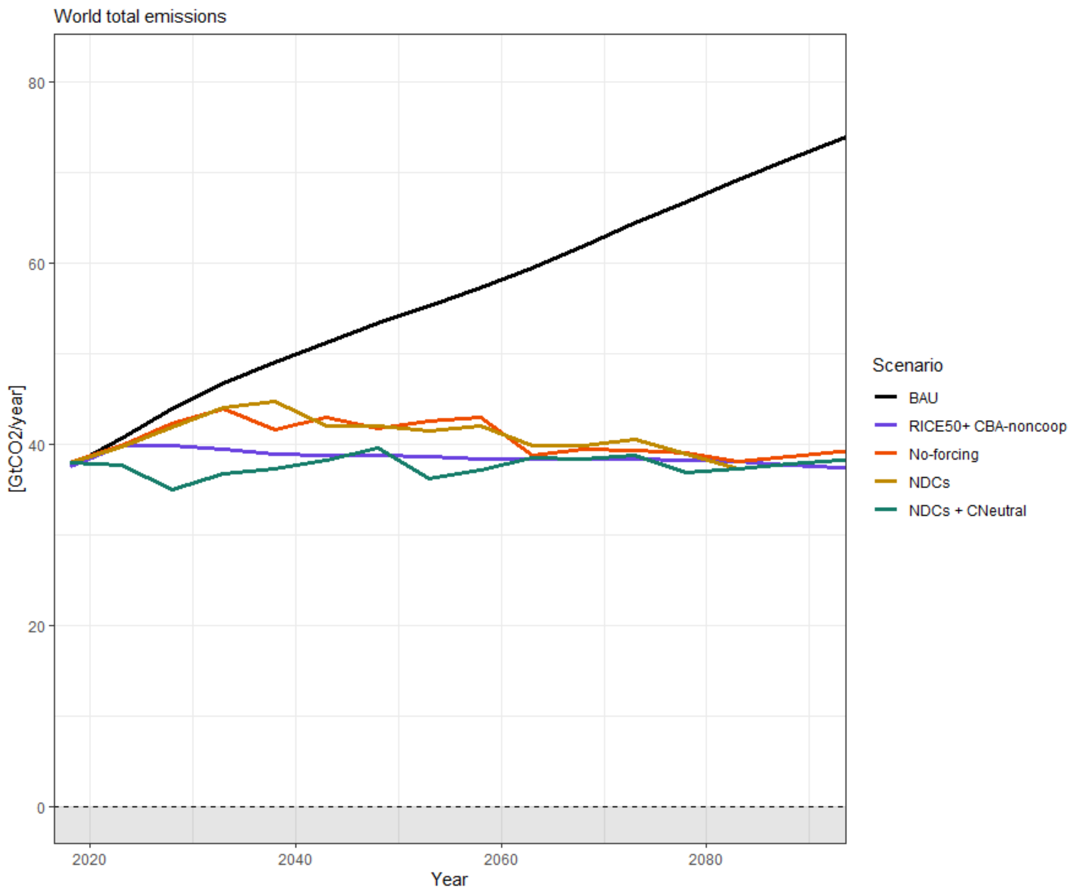


Figure 4.6: World total emissions according to the scenarios defined. Trajectories are the result of several repeated negotiations.

4.5 Discussion and conclusions

In this paper, we presented a novel agent-based framework, intended to support the investigation of bottom-up IEAs formation and cooperation incentives. We provided a comprehensive definition for all its main dynamics, interactions, and decision-making components that characterize each individual agent. We discussed some first calibration options, based on non-cooperative projections from the RICE50+ IAM, NDCs commitments for the year 2030, and recent public carbon-neutrality declarations. We eventually attested the appropriate model response in some meaningful scenarios.

Starting from the building blocks definition, this model aims to reproduce the complex phenomena of international negotiation under several and potentially conflicting decision-makers. It follows a natural and descriptive approach, suitable for including significant regional heterogeneities and, at the same time, offering a high level of flexibility. The described framework is indeed highly scalable to an increasing number of agents, the definition of new decision-forcing components, the improvement of interaction rules, and a more detailed representations for local economies or climate feedbacks.

Presented preliminary results show the framework capability of taking different evolutions when accounting for additional decision forces. Small changes in private agents' evaluations may lead the negotiations towards new and potentially distant agreement outcomes. The model can be improved in this direction by defining more sophisticated decision-making processes within each agent. They include, for example, a better counting of private non-economic payoffs, varied risk-aversion dispositions that lead to different evaluations of the same policies, and an improved account for co-benefits that may foster individual commitment (cf. Finus, 2008). Other future improvement directions may also address agents' data interpretation, the selection of private rules to decide upon multi-objective tradeoffs, and additional persuasion arguments included in the negotiation process. The modelling of potentially cheating behaviours (e.g., countries that decide not to comply with their agreed commitments) may be of significant interest as well.

Preliminary results shown in this paper favourably suggest that analyses of the emerging behaviours of the complex model bottom-up dynamics may support the research of the most influential conditions and levers for international cooperation.

Last but not least, it is necessary to point out some important caveats. First of all, as already anticipated, the proposed framework cannot rely on proper validation due to the lack of sufficient undisclosed data and time series of past COP negotiations. Moreover, despite all the possible improvement efforts, it may always remain a conceptualized *oversimplification*: real-world negotiators not only debate upon quantity-based proposals but also fight on final-treaty-text words and their intended interpretation.

However, the preliminary results favourably suggest that analyses of the emerging behaviours of the complex model bottom-up dynamics may support the research of the most influential conditions and levers for international cooperation. As already pointed out by Earnest (2008), *agent-based modelling is no substitute for empirical studies or for the deduction of game theory*, yet it could still represent an important and effective tool to explore alternative behavioural scenarios and get complimentary insights to other more-consolidated models.

4.6 Code availability

Full Python code will be provided open access once published.

4.7 References

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4.A Negotiation algorithm

Algorithm 1: Sequence of mediator actions

```
Announces new negotiation;
Gather participants and ask them to get ready;
Ask for first proposal ;
Collect all proposals ;
while agreement not found do
    Share received proposals to all the participants;
    Ask for updated proposal;
    Collect all proposals ;
Arrange agreement information;
Share information and ask for ratification;
```

Algorithm 2: Sequence of agent actions

```
Receive negotiation announcement ;
Evaluate a new private strategy ;
Determine and share first proposal ;
Receive round result ;
Update negotiation memory ;
while agreement not found do
    Update strategy parameters ;
    Determine and share an updated proposal ;
    Receive round result ;
    Update negotiation memory ;
Receive agreement information ;
Update agreement memory ;
Ratify agreement ;
```

4.B Economies equations

Here follows a short listing of main equations for agents economy. As they all are derived from RICE50+ model, refer to Gazzotti (2021) for detailed explanations on merit.

GDP output is computed through a Cobb-Douglas production function of capital $K_i(t)$ and SSPs-calibrated labour $L_i(t)$ and total factor productivity $\mathrm{TFP}_i(t)$:

$$Y_{\mathrm{GROSS},i}(t) = \mathrm{TFP}_i(t) \cdot K_i(t)^{\alpha} \cdot L_i(t)^{1-\alpha}. \tag{4.8}$$

Savings rates $S_i(t)$ are set at their optimal projected values for baselines. They determine investments and capital accumulation according to equations:

$$I_i(t) = S_i(t) \cdot Y_i(t) \tag{4.9}$$

and:

$$K_i(t+1) = (1-\delta_k)^{\Delta t} \cdot K_i(t) + \Delta t \cdot I_i(t). \tag{4.10}$$

The impact factor is applied as GDP discount on the basis of local temperature variation:

$$Y_{\mathrm{NET},i}(t) = \frac{Y_{\mathrm{GROSS},i}(t)}{\Omega_i(t, T_{\mathrm{region}})}. \tag{4.11}$$

The discount-factor Ω is determined by empirically estimated impact functions as shown in detail in Gazzotti (2021).

Variable $Y_i(t)$ is net GDP obtained by subtracting abatement costs $\Lambda_i(t, \mu_i)$ to GDP net-of-damages $Y_{\mathrm{NET},i}(t)$:

$$Y_i(t) = Y_{\mathrm{NET},i}(t) - \Lambda_i(t, \mu_i). \tag{4.12}$$

4.C Model regions and countries mapping

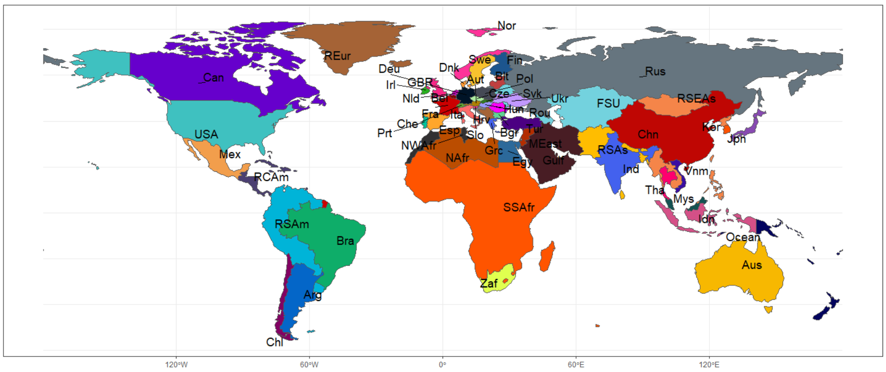

Figure 4.7: Geographical representation for defined agents. They correspond to RICE50+ model regions.

Chapter

5 Conclusions

This doctoral dissertation addressed the problems of heterogeneities representation in BC-IAMs and distributed decision-making modelling in climate change international agreement negotiations. In particular, it comprises advancements both in the development of technical solutions and in the related policies assessments and dicussion. The presented contribution focused on three main research questions, put in a linear progression.

The first research question was about an effective improvement of benefit-cost policy-optimizing Integrated Assessment Models to follow the latest science, data availability, and properly account for regional heterogeneity. In Chapter 2 we hence introduced RICE50+, a Benefit-Cost optimizing Integrated Assessment Model with an unprecedented number of independent regions. It accounts for differentiated and calibrated abatement cost curves and recent empirically estimated impact functions with a high level of heterogenity.

Then, it directly followed the second research question about the optimal policies that would be the outcome of such a heterogeneous model. In particular, we wanted to investigate how cross-countries inequality would have been affected by climate change and to which extent optimal policies could improve the general outlook. In Chapter 3 an extensive analysis on optimal policies and related consequences was provided. Inequality notably emerged as a critical aspect since it persists, due to climate change impacts, also in optimal mitigation scenarios with a high level of international cooperation. Ambitious mitigation policies confirm to be strongly necessary to stabilize the temperature increasing, but also that they alone are not sufficient to close the gap of disparities among regions. Economic progress needs to be both sustainable and inclusive, and oriented towards resilient climate adaptation policies.

Eventually, we addressed the problem of conceptualizing the multi-faceted strategies and decision forcings that take place in international negotiations (and that are exacerbated by discussed heterogeneities). Hence, we asked ourselves how to better model the complex dynamics of International Environmental Agreement formation and negotiation. And, furthermore, which modelling tools could provide sufficient flexibility, yet informative insights, to explore the distributed decision-making process. In Chapter 4 we hence defined a novel agent-based negotiation framework for the simulation of international negotiations. It follows a bottom-up approach and starts from the definition of individual behaviours and their interaction rules, reproducing a very complex dynamic from its building blocks. The RICE50+ model and its associated optimal-projections data represent two essential enabling steps for this new modelling solution.

In the closing remarks of this thesis, it goes without saying that the research questions in the framed context are far from being exhausted. On the contrary, several research directions now open. The RICE50+ model can be used for new assessments of important economic indicators such as a regionally differentiated Social Cost of Carbon (see Ricke et al., 2018 and R. S. Tol, 2019). New definitions or calibration improvements for its key aspects can lead to different and highly informative benefit-cost projections. They include, for example, endogenous technically-induced abatement costs (e.g., see Bosetti et al., 2008; Popp, 2004; van der Zwaan et al., 2002,), adaptation options (e.g., see Bruin, Dellink and R. S. J. Tol, 2009), or multi-objective trade-offs in the welfare function (e.g., see Bauer et al., 2020).
In addition, as a consequence of the inter-regional inequality assessment presented, it follows a research question on the climate change effects on intra-regional inequalities. Modelling distributional differences within regions of both consumption and damages (e.g., following Dennig et al., 2015 approach) could lead to highly valuable benefit-cost assessments and policy indications.
Last but not least, the ABM negotiating framework is just at its early stages. It will be used and customized in future researches to simulate and investigate a large variety of potential geo-political settings. It will be used both in support of consolidated game-theory models and as a self-standing tool for new scenario-exploration purposes, searching for the most strategical policy indications to fight climate change.

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