RICE50+: DICE model at country and regional level

Paolo Gazzotti[1,2]*

[1] Department of Electronics, Information, and Bioengineering, Politecnico di Milano, Milan, Italy
[2] RFF-CMCC European Institute on Economics and the Environment (EIEE), Centro Euro-Mediterraneo sui Cambiamenti Climatici, Milan, Italy

Abstract

Benefit-cost Integrated Assessment Models (IAMs) have been largely used for optimal policies and mitigation pathways countering climate change. However, the available models are relatively limited in the representation of regional heterogeneity. This is despite strong evidence of significant variation of local mitigation costs and benefits, institutional capacity, environmental and economic priorities. Here, I 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, alternative 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.

Keywords

climate change; integrated assessment model; benefit-cost analysis; climate policy

Code and Data Availability

All code for the described model can be accessed at: https://github.com/witch-team/RICE50xmodel. All data used for the illustrative results and code to reproduce following figures can be accessed at: https://github.com/witch-team/RICE50xmodel/releases/download/v1.0.0/SESMO_results_dataset.zip.

1. Introduction

As time passes, climate change has become one of the most important and challenging global problems, with severe potential consequences for natural ecosystems and human societies. In its last reports (IPCC, 2018; IPCC, 2021), the Intergovernmental Panel on Climate Change once more called for immediate and ambitious mitigating actions. Among the models that climate scientists and economists use to inform policymakers on climate policies, Integrated Assessment Models (IAMs) play a significant and influential role (e.g., see Weyant et al., 1996; Weyant, 2014, 2017). These models are called integrated due to the different subject areas – economy, energy, and climate – interconnected within a common framework.

Correspondence:
Contact P. Gazzotti at paolo.gazzotti@polimi.it

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Weyant (2017) classifies IAMs into two main categories: detailed process (DP) and benefit-cost (BC). DP-IAMs usually provide more information as they include: economic sectors, a high degree of geographical disaggregation, and a more complex system for physical feedbacks. Their main usages comprise the analyses of climate impacts, mitigation, and interactions between impact sectors under mitigation and adaptation policies. BC-IAMs, on the other hand, aggregate the physical impacts, the economic costs of climate change, and the benefits of GHG emissions mitigation. They are extensively adopted to perform long-term optimal assessments, which are usually too onerous and time-consuming applications for the complexity of DC-IAMs. These assessments notably include: (1) the evaluation of long-term optimal trajectories for global GHG emissions (i.e., balancing the marginal cost against the marginal damages resulting from the last ton emitted), (2) the assessment of corresponding policy-equivalent prices to charge for those emissions, (3) the evaluation of additional costs of nonoptimal climate policies, and (4) the estimation of the Social Cost of Carbon (SCC), an important indicator of the marginal damage caused by an additional ton of carbon emissions (cf. Weyant, 2014). Weyant (2017) illustrates some significant limitations and key improvement directions for this modelling research field.

This paper focuses on the crucial aspect of regional socio-economic heterogeneity representation in BC-IAMs. Popular BC optimizing models like RICE (Nordhaus, 2010; Nordhaus & Yang, 1996), PAGE (Hope, 2008), FUND (Anthoff, 2009), C^3 IAM (Wei et al., 2020), CWS (Eyckmans & Tulkens, 2003), WITCH (Bosetti et al., 2006), MICA (Lessmann et al., 2015), and STACO (Nagashima et al., 2009), execute from 6 up to 16 independent regions only. Despite the coherent grouping criteria applied, this may raise some legitimate doubt on their capability of properly capturing local growth differences, climatic vulnerabilities, and mitigation costs, as they all significantly vary across countries (van den Berg et al., 2020).

In fact, and most notably, recent and debated empirical evidence on climate economic impacts point out strong heterogeneities across countries, with potential winners and losers related to local temperature deviations (e.g., see Burke et al., 2015; Dell et al., 2012; Diffenbaugh & Burke, 2019; Kahn et al., 2019). They also esteem significant higher impacts than previously expected. However, I have found only a few attempts of implementing these studies as BC-IAMs impact functions in the literature so far. Glanemann et al. (2020) implement the general rule found by Burke, Hsiang, and Miguel (2015) –hereafter BHM– in DICE, but, given the single-region nature of this model, they had to fit an aggregated response to the global mean temperature increase. Moore & Diaz (2015) implement the impact function by Dell, Jones, and Olken (2012) –henceforth DJO– in a two-region-only extension of the DICE model. Ricke et al. (2018) provide country-level impact projections linked to local temperatures but do not apply any optimizing framework. To the best of my knowledge, no implementation of these empirical impact functions has been introduced in any BC-IAMs that accounts for an adequate number of regions yet.

Besides impacts, abatement cost curves also vary remarkably across regions, as they depend on specific local conditions (e.g., local fuel prices, wind and solar potential, insolation; cf. Gillingham & Stock, 2018). Detailed-Process model outcomes are therefore extensively used to calibrate the marginal abatement costs curves (MACCs) in benefit-costs optimizations. However, when a high level of aggregation is applied, their regionally differentiated expressivity undoubtedly reduces (e.g., see Weyant, 2017; Hänsel et al., 2020).

Impacts and costs allow, then, to estimate another important economic variable: the Social Cost of Carbon (SCC). Defined as the incremental impact related to the emission of an additional ton of carbon dioxide, when evaluated on optimal emissions trajectory, the SCC reveals the equivalent carbon tax required to restore efficiency. Recent contributions of Ricke et al. (2018) and Tol (2019) notably show how SCC differ significantly across different countries.

Last, spatial heterogeneity also has strong repercussions on efforts coordination (e.g., see Keohane & Victor, 2016; Li & Rus, 2019; 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 on the estimation of counterfactual scenarios. In fact, these are usually based on Business-As-Usual (BAU) assumptions, which account for no mitigation at all. However, recent criticisms point out how these scenarios lead to implausibly high emissions (Peters, 2016), whereas a more adequate counterfactual reference entails countries that react to climate impacts based on their pure self-interest. In the context of international climate negotiation, it corresponds to a non-cooperative game-theoretic assumption.

Here I present a new regional model, called RICE50+, which originates from the well-known Nordhaus' DICE model and aims at tackling these gaps. RICE50+ was developed with the aim to provide a benefit-cost optimizing tool that explicitly focuses on cross-region dynamics, with unprecedented detail for major heterogeneity components. What follows provides a general description of the model and illustrates all the original contributions in its main dynamics, data integration and calibration. Some examples, showing representative model outputs and a sensitivity analysis over main benefit-cost drivers importance, complete the technical description.

2. Model description and calibrations

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

I started from Nordhaus' Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1994, 2010), among the simplest yet most used and known benefit-cost IAMs. I chose not to start from RICE (Nordhaus & Yang, 1996) as it is older and oversophisticated. Hereafter I always refer to its latest DICE-2016R2 formulation, used by Nordhaus (2018), unless otherwise stated. The RICE50+ model is written in GAMS (GAMS Development Corporation, 2013) 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.

2.1 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 closing period with total-consumption and no investments or mitigation policies to boost solution welfare performance), run horizon goes up to the year 2300. Meaningful projections outcomes are then extracted from the 2015-2100 interval only.

Figure 1 shows all the independently-deciding regions of RICE50+. They have been chosen according to the finest detail available from local abatement costs data retrieved from POLES model (Després et al., 2018), as I will better illustrate in dedicated Section 2.4. Almost all the most influential economies are represented as single-country regions. Note how also the European Union is accounted as single member-states (but I included the possibility to group them together, acting as a single player). Largest country-groups left are: those aggregating states of Persian Gulf (Gulf), Sub-Saharan Africa (SSAfr) and middle East (MEast); members of the former Soviet-Union (FSU); and secondary players of Latin-America (RSAm) and South-East-Asia (RSEAs). Sub-Saharan Africa, notably, is the widest geographical and political aggregation left. Unfortunately, it reflects the lack of detailed data as well as the high uncertainties currently concerning several African economies. I plan to further subdivide this in future model updates, as soon as more detailed data will become available. See also Table S1 in the Supplementary Material for a full mapping between model regions and their ISO3 countries.

2.2 Economy and projections

RICE50+ regional economies largely inherit from Nordhaus' DICE/RICE models' representation. GDP outputs are expressed in Purchasing Power Parity (PPP), which means they adjust for price differences, providing a correct comparison of income levels across countries. GDP gross output $Y_{\mathrm{GROSS},i}(t)$, for region *i* at each timestep t, is the result of a Cobb-Douglas production function in capital $K_i(t)$, labour $L_i(t)$ and total factor productivity $\mathrm{TFP}_i(t)$:

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

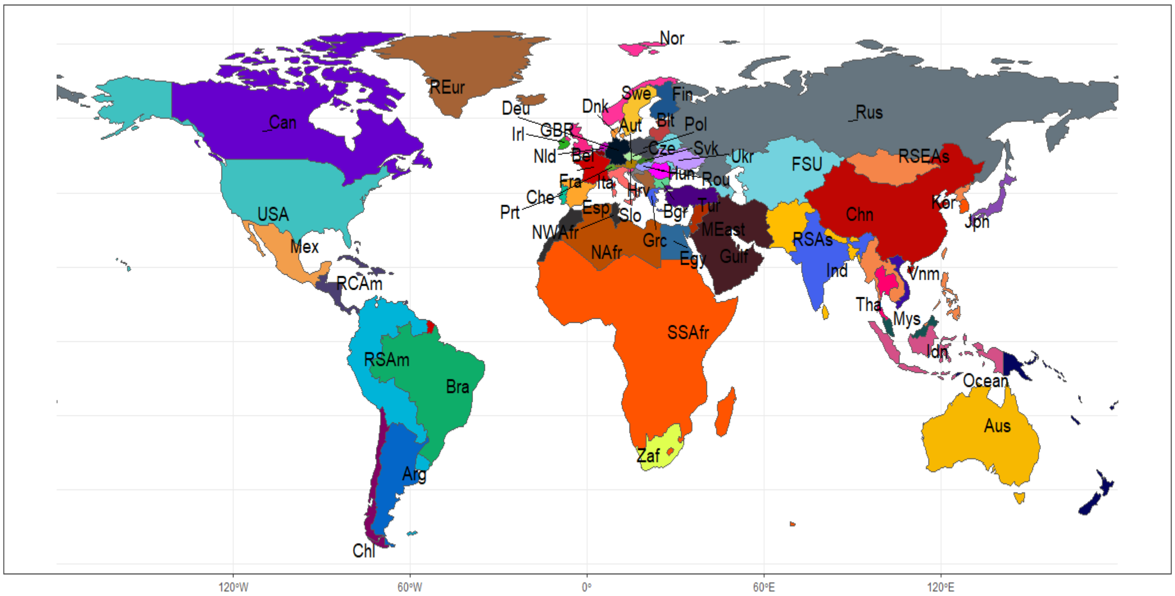

Figure 1: Geographical representation for RICE50+ model regions. Subdivision reflects the finest available resolution for local abatement cost curves.

Labour and TFP have exogenous trends, calibrated to match the Shared Socio-economic Pathways (SSPs) (O'Neill et al., 2014; Riahi et al., 2017) population and GDP-growth projections. Hence, the model can execute 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), I followed a conservative approach. I extrapolated the growth-rates from last available time-period for both population and GDP, and I 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 the current century. Figure S1 in the Supplementary Material shows stacked projections for both regional population and GDP in a SSP2 scenario.

In benefit-cost optimizing models, the savings rates $S_i(t)$ are usually left as free variables to be evaluated by the solver. They determine regions' internal investments, and consequent capital formation according to the equations:

$$I_i(t) = S_i(t) \cdot Y_i(t), \tag{2}$$

and:

$$K_i(t+1) = (1 - d_k)^{\Delta t} \cdot K_i(t) + \Delta t \cdot I_i(t). \tag{3}$$

Variable $Y_i(t)$ represents the final GDP output accounting for climate-change impacts $\Omega_i(t)$, and abatement costs $\Lambda_i(t, \mu_i)$ that are related to mitigation decisions $\mu_i(t)$:

$$Y_i(t) = \frac{Y_{\text{GROSS},i}(t)}{\Omega_i(t)} - \Lambda_i(t, \mu_i). \tag{4}$$

In RICE50+, I 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 models; 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 results as a function of capital elasticity in production function α, depreciation rate on capital per year d_k, elasticity over the marginal utility of consumption η, elasticity of output to capital ζ, and pure rate of social time preference ρ (also known as utility discount rate):

$$\overline{S} = \alpha \cdot \frac{(d_k + \zeta)}{(d_k + \zeta \cdot \eta + \rho)}. \tag{5}$$

Table 1 shows all default values for these parameters, following DICE-2016R2 formulation (Nordhaus, 2018). A discussion on the highly influential parameters of discount rate ρ and elasticity over the marginal utility of consumption η follows in Section 2.7, dedicated to the social welfare function. Last, note that the savings rate definition lets regions invest only internally. I chose to keep this limitation for the moment, given the complexity of modelling cross-region capital flows. Future improvements of the model may address this point more adequately.

Table 1: Default values for main economic normative parameters (cf. DICE-2016R2).

Parameter	Default value	Description
d_k	0.1	Depreciation rate on capital per year
α	0.3	Capital elasticity in production function
ζ	0.004	Elasticity of output to capital
η	1.45	Elasticity over the marginal utility of consumption
ρ	0.015	Pure rate of social time preference (i.e., discount rate)

2.3 Emissions and carbon-intensity calibration

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

$$E_{\text{IND},i}(t) = \sigma_i(t) \cdot Y_{\text{GROSS},i}(t) \cdot (1 - \mu_i(t)). \tag{6}$$

The control variable $\mu_i(t)$ represents regions' emissions-mitigation choice (expressed in percentage units). As in the original DICE definition, and for the sake of simplicity, I assumed that the control rate $\mu_i(t)$ implicitly encompasses technological change, while carbon-intensity $\sigma_i(t)$ is kept exogenous (hence, same limitations and caveats apply, e.g., see Nordhaus, 2008). Future model developments will try to endogenize the technological change effect (e.g., following Bosetti et al., 2008; Popp, 2004; van der Zwaan et al., 2002).

To calibrate exogenous $\sigma_i(t)$ I started from the DICE carbon-intensity definition, applied to each region:

$$\sigma_i(t+1) = \sigma_i(t) \cdot \exp(\, g_i(t) \cdot \Delta t), \tag{7}$$

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

$$g_i(t+1) = g_i(t) \cdot (1 + d_i)^{\Delta t}. \tag{8}$$

Although DICE model has a single trend for its carbon-intensity, in RICE50+ it varies according to SSP-reference. I therefore assumed DICE trend as representative for middle-of-the-road SSP2 baseline, and hence I calibrated $\sigma_{\text{ssp},i}(t)$ following a two-step process. First, I assessed its parameters' values to best match the SSP2 baseline, then I proportionately determined other-SSP values accordingly.

To best match the SSP2 baseline I imposed, for all curves of eq. (7), their passage through known 2015 levels. Then, I 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 from eq.(6), by imposing $\mu_i(t) = 0$), EnerData MACC emission baselines (available for 2025-2040 period, as described later in dedicated Section 2.4), and regional emission-projections from SSP2-marker-model (MESSAGE-GLOBIOM, available for 2015-2100 period). Beyond 2100 I 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 for SSP2 results as a convex-combination of two components:

$$\sigma_{\text{ssp2},i}(t) = (1 - \text{cc}(t)) \cdot \overline{\sigma_i}(t) + \text{cc}(t) \cdot \sigma_{\text{DICE}}(t), \tag{9}$$

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

As a second step, I evaluated carbon-intensities also for other socio-economic scenarios. I added $m_i(ssp)$, an SSP-dependent multiplier, in eq. (7), also accounting for previously optimized $\overline{g_i}(t)$ term:

$$\sigma_i(ssp, t+1) = m_i(ssp) \cdot \sigma_i(ssp, t) \cdot \exp(\, \overline{g_i}(t) \cdot \Delta t). \tag{10}$$

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

$$\sigma_i(ssp,t) = (1 - \mathrm{cc}(t)) \cdot \widehat{\sigma_i}(ssp,t) + \mathrm{cc}(t) \cdot \xi(ssp) \cdot \sigma_{\mathrm{DICE}}(t). \tag{11}$$

Correction factor:

$$\xi(ssp) = \frac{\hat{\sigma}_{\mathrm{World},2100}(ssp)}{\overline{\sigma}_{\mathrm{World,ssp2},2100}} \tag{12}$$

reflects the resulting proportion, in year 2100, between each SSP world-aggregated carbon-intensity (from calibrated values) and the SSP2 one.

Regions can reduce their baseline emissions by increasing their choice over percentage mitigation $\mu_i(t) \in [0\%, 120\%]$. Unlike the original DICE/RICE, I introduced limitations on the maximum mitigation increasing rate. Following assumptions as in Hänsel et al. (2020), I fixed a 20% maximum increase every (5-years) period. As a direct consequence, negative emissions (ranging from 100% to 120% mitigation as in the 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 reversion of emissions to BAU levels.

2.4 Abatement costs and MAC curves

To determine the regional Marginal Abatement Cost (MAC) curves I differentiated between three time periods. For the near future (2025-2040), I fitted continuous curves on EnerData-EnerFuture data projections, retrieved from the detailed process-based model POLES, an energy-sector model jointly developed with the European Commission (Després et al., 2018). For the rest of the century, I 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 trend, driven by a backstop technology.

As previously mentioned, and shown by Figure 1, the MACC dataset has significant higher detail for European countries, with coarser aggregations for African, South-East Asian, and Latin American ones. Despite it being the most granular dataset of this kind (at the moment of RICE50+ definition), I acknowledge this could lead to a potential European bias and, therefore, a potential limitation. I commit to improving the model on this aspect when better and more detailed datasets become available.

2.4.1 Data-driven phase

To evaluate the individual abatement cost curves, I started from EnerData-EnerFuture MAC data, which provide, for each region, industrial CO_2 projected reductions for several carbon-price levels over the 2025-2040 period. First, I identified the best continuous curve fitting those data. I compared R-squared goodness measures for different candidate curves (see Figure S2a in Supplementary Material C), and I analyzed qualitatively their performances for the most influential economies (Figure S2b in Supplementary Material C shows curves for the China region, as a representative example). A fourth-exponent polynomial curve turned out to be the best-matching model:

$$C_{\mathrm{PRICE},i}(t,\mu) = a_i(t)\mu_i + b_i(t)\mu_i^4. \tag{13}$$

I extended the region-specific $a_i(t)$ and $b_i(t)$ coefficients also to time-steps not directly covered by EnerData projections. This preserves a primal differentiating component among different regions. Then, I 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 (i.e., Riahi et al., 2017; IPCC, 2018):

$$\mathrm{MAC}_i(t,\mu) = \nu_i(t) \cdot (a_i(t)\mu_i + b_i(t)\mu_i^4). \tag{14}$$

I first exploited the $\nu_i(t)$ multiplier to harmonize the calibrated curves with the SSP-models ones to increase general consistency (i.e., limit the risk of overfitting to the POLES model assumptions). To this end, I extracted the MAC curves from the SSPs database, using policy scenarios with different carbon-price projections. I used those curves to evaluate the best value $\overline{\nu}(t)$, equal for all regions, which minimizes the difference between RICE50+ globally abated emissions and the correspondent SSP ensemble's median levels.

2.4.2 Backstop phase

For the long-term period, given the absence of any regional-detailed projection, I decided to follow the original DICE model, by adopting an exogenous global backstop (i.e., carbon-free technology whose cost depends on R&D investments, cf. Nordhaus, 2008; Bosetti & Tavoni, 2009) curve. It is defined as:

$$\mathrm{BT}(t) = pback \cdot (1 - gback)^{t-1}, \tag{15}$$

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

After an intermediate transition phase (described in the following subsection), from time $t \geq t_{\mathrm{BT}}$ I imposed to match backstop values for a 100% mitigation level ($\widehat{\mu_i} = 1$) for each regional MAC curve, obtaining correction factor $\widehat{\nu_i}(t)$ values accordingly:

$$\widehat{\nu_i}(t) \cdot \left(a_i(t)\widehat{\mu_i} + b_i(t)\widehat{\mu_i}^4\right) = \mathrm{BT}(t)|_{t \geq t_{\mathrm{BT}}}. \tag{16}$$

2.4.3 Transition phase

Transition towards a common backstop curve begins in 2045 (first timestep 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 $\overline{t} = 2040$) to $\widehat{\nu_i}(t)$ (for $t = t_{\mathrm{BT}}$) according to:

$$\nu_i(t) = \widehat{\nu_i}(t) - \mathrm{cb}(t) \cdot \max(\widehat{\nu_i}(t) - \overline{\nu_i}(t), 0). \tag{17}$$

Transition coefficient $\mathrm{cb}(t)$ follows a smooth sigmoid dynamic (a commonly used functional form for transitional technology, e.g., see Rogers, 2010):

$$\mathrm{cb}(t) = \frac{1}{1 + e^{-k \cdot \left(t - \frac{1}{2}(t_{\mathrm{BT}} - \overline{t})\right)}}, \tag{18}$$

where parameter k affects general transition speed and smoothness. I qualitatively selected k and t_{BT} after evaluating several tests and comparing model responses to increasing carbon-tax policies with the SSPs models ensemble. Figure S3 in Supplementary Material C shows an example for this qualitative evaluation.

2.4.4 Final abatement costs

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

$$\Lambda_i(t, \mu_i) = \int_0^{\mu_i} E_{\mathrm{BAU},i}(t) \cdot \mathrm{MAC}_i(t, \mu_i)\, d\mu, \tag{19}$$

where $E_{\mathrm{BAU},i}(t)$ represents regions' baseline industrial emissions, as from eq. (6) in absence of mitigation ($\mu_i(t) = 0$). Therefore, from the integration of eq. (14), it follows that in RICE50+ abatement costs are ultimately evaluated as:

$$\Lambda_i(t, \mu_i) = \nu_i(t) \cdot E_{\mathrm{BAU},i}(t) \cdot \left(\frac{a_i(t)}{2}\mu_i^2 + \frac{b_i(t)}{5}\mu_i^5\right). \tag{20}$$

2.5 Global and local climate

The atmospheric concentrations of greenhouse gases are obtained by modelling the equations of the carbon cycle for three reservoirs (atmosphere, the upper oceans and biosphere, and the lower oceans, respectively) as in the original DICE family of models (e.g., see Nordhaus, 2008; 2018). $\mathrm{CO_2}$-effect on radiative forcing $\mathrm{RF}_{\mathrm{CO_2}}(t)$ is then determined by its changes in the atmospheric concentration $M_{\mathrm{CO_2}}(t)$ from the pre-industrial reference level $M_{\mathrm{CO_2,pre}}$ as follows:

$$RF_{\mathrm{CO_2}}(t) = \mathrm{a_m} \cdot \ln\left(M_{\mathrm{CO_2}}(t)/M_{\mathrm{CO_2,pre}}\right) \tag{21}$$

Then, total forcing results from equation:

$$RF(t) = RF_{\mathrm{CO_2}}(t) + RF_{\mathrm{OGHG}}(t), \tag{22}$$

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

In most climate-economy IAMs, climate variables are considered only at the global level, mainly due to computational reasons. However, in RICE50+ regional temperature responses to greenhouse gas emissions are also needed to assess the heterogeneous warming impacts across countries. For this purpose, I used the CMIP5[1] database (Taylor et al., 2011) to implement a calibrated statistical downscaling method. Data provide historical projections for temperature and precipitation at the 0.5° gridded level on an average annual basis. Values were aggregated to the country level using population weights, preferred over spatial weights to capture better the impact on people (i.e., for large countries like China or Canada, where the population concentrates unevenly on a smaller portion, it may be significant). I used the population values from the year 2000 kept fixed over time (as done by Burke et al., 2015; 2018), obtaining observations for $N = 244$ countries and territories.

Then, from different representative concentration pathways (RCPs), implemented by several global climate models, I considered the mean of model ensemble to link the global-mean-temperature increase ($\Delta\mathrm{GMT}$) to the country-level average annual temperature. This procedure was repeated for all the RCPs. Finally, I ran a linear regression (cf., e.g., Mitchell, 2003; Giorgi, 2008) 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):

$$T_n(t) = \mathrm{p}_n + \mathrm{q}_n \Delta\mathrm{GMT}(t) \tag{23}$$

The R^2 goodness measure for the estimated regressions varies between 0.95 and 0.999. The equivalent p_i and q_i coefficients for RICE50+ model regions (which determine local temperatures $T_i(t)$) are the population-weighted average of the p_n and q_n values for the associated countries, due to their linear relationship.

2.6 Other GHG and land-use effect

Land-use (LU) and other greenhouse gases (OGHG) are not the primary focus of this model. Therefore, I decided to keep them simple exogenous effects (as in the original DICE formulation) with a few minor adjustments.

OGHGs are modelled as an additional forcing RF_{OGHG} that sums to the CO_2-related $RF_{\mathrm{CO_2}}$ to generate final climate forcing $RF(t)$ (see eq. (22)). I extracted data for both forcing components from SSPs models (Riahi et al., 2017), accounting for all baseline and policy experiments. I found that these two components can be linked by a linear model, under an acceptable approximation ($R^2 = 0.608$). Therefore, in RICE50+ the additional OGHG effect is directly estimated from CO_2 forcing by the following linear regression:

$$RF_{\mathrm{OGHG}}(t) = r \cdot RF_{\mathrm{CO_2}}(t) + s, \tag{24}$$

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

To calibrate the regional land-use effect, I obtained the initial $E_{\mathrm{LU},i}(t_0)$ values by aggregating PRIMAP historical country-level database (Gütschow et al., 2016). I took the mean values between 2010 and 2015 to reduce the impact of historical fluctuations (quite common in LU emissions). Then, I kept the DICE original decreasing trend and applied it to each region:

$$E_{\mathrm{LU},i}(t) = E_{\mathrm{LU},i}(t_0) \cdot (1-d)^{t-1}. \tag{25}$$

Starting from this general rule, I introduced two alternative behaviors. In the first one, all countries equally follow the decreasing trend. High-emitting countries will lower their emissions over time, while already negative-emitting countries will increase their contributions towards the common zero-value asymptote. Under this behavior, cumulative LU emissions result in an almost perfectly equivalent global DICE2016-R2 effect. This behavior applies to non-mitigative BAU experiments. In the second case, only countries with positive initial values follow the decreasing trend, while already negative-emitting ones keep their $E_{\mathrm{LU},i}(t_0)$ levels constant. This behavior leads to a more ambitious cumulative effect and applies in benefit-cost optimizations.

2.7 Climate impact functions

The classical approach, used in most IAMs, consists in calibrating a region-specific damage curve, typically based on global mean temperature increase. Projected impacts from climate change often include factors like sea-level rise, increased energy demand, and agricultural productivity changes. Non-market damages, like

[1] An appropriate database for statistical downscaling based on CMIP6 results was not available at the time of model construction. I plan on updating it in future releases.

ecosystem losses and non-market health impacts, are also often considered. Regional impacts are thus usually computed using a damage function which depends on global mean temperature $\mathrm{GMT}(t)$ as follows:

$$\Omega_i(T(t)) = a_{1i} \cdot \Delta\mathrm{GMT}(t) + a_{2i} \cdot \Delta\mathrm{GMT}(t)^{a_{3i}}, \tag{26}$$

where a_{1i}, a_{2i}, a_{3i} are calibrated, region-specific coefficients. The impact factor Ω_i, in turn, leads to a GDP reduction (or a consumption reduction, depending on the model):

$$Y_{\mathrm{NET},i}(t) = \frac{Y_{\mathrm{GROSS},i}(t)}{\Omega_i(t)}. \tag{27}$$

This approach has some drawbacks. A noteworthy contribution comes from Weitzman (2009), who criticizes classical IAMs impact functions, arguing that their extrapolation is hardly well justified. That is due to the high nonlinear effects of GHG-induced warming, which lead to fat-tails on the probability density function. That implies the possibility of catastrophic events (i.e., tipping points) that may produce, although with low probability, harm so great that would be difficult to compensate by ordinary savings. Furthermore, he also notices how these functions are usually calibrated upon observations at low degrees of warming, and therefore hardly empirically justifiable, as "*almost anything can be made to fit the low-temperature damages assumed by the modeller*" (Weitzman, 2009).

Moreover, there is also general disagreement in the scientific community on whether temperature feedbacks affect the *level* of GDP production or its *growth* (e.g., see Schlenker & Auffhammer, 2018). Classical IAMs functions, that affect solely the level, have been criticized as potentially underestimating the full impacts for the long-run growth of the economy (e.g., Pindyck, 2013). On the other hand, the uncertainty is greatest for models that specify the effects of temperature on GDP growth, as recently assessed by Newell et al. (2021).

In the RICE50+ model, I chose to take both the growth and level assumptions as alternative options. In addition to the classical DICE formulation, which follows eq. (24) and can be regionally calibrated as in RICE (e.g., see Nordhaus & Yang, 1996), I added other formulations based on recent empirically estimated impact functions. Different specifications of linear impacts $\delta_{i,\mathrm{spec}}(t)$ on the GDP per-capita baseline growth rate $\mathrm{g}_i(t)$ have been considered for this purpose, as described in the rest of this section. According to this formulation, GDP per-capita production between periods t and $t+1$ can be written as:

$$\mathrm{GDP}_{\mathrm{CAP},i}(t+1) = \mathrm{GDP}_{\mathrm{CAP},i}(t)(1 + \mathrm{g}_i(t) + \delta_{i,\mathrm{spec}}(t)). \tag{28}$$

This translates into DICE notation as follows: $\mathrm{GDP}_{\mathrm{CAP},i}(t) = \frac{Y_{\mathrm{NET},i}(t)}{L_i(t)}$; thus, replacing the classical impact definition of eq. (25), and then equations (1), (2), (3), I obtained a new recursive formula for impacts $\Omega_i(t)$:

$$\Omega_i(t+1) = \frac{\mathrm{TFP}_i(t+1)}{\mathrm{TFP}_i(t)}\left(\frac{L_i(t+1)}{L_i(t)}\right)^{-\alpha} \cdot \Upsilon_i(t)^{\alpha} \cdot \frac{1+\Omega_i(t)}{(1+\mathrm{g}_i(t)+\delta_{i,\mathrm{spec}}(t))^{\Delta t}} - 1, \tag{29}$$

where:

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

This implementation is perfectly consistent with the growth-rate empirical impact estimation of eq. (26). However, it can lead to numerical issues, notably when the model optimizes policies with an endogenous savings rate. Therefore, I also implemented an alternative approximate rule $\tilde{\Omega}_i(t)$, equivalent to the standard $\Omega_i(t)$ in DICE:

$$\tilde{\Omega}_i(t+1) = (1+\tilde{\Omega}_{it})\frac{1}{(1+\delta_{i,\mathrm{spec}}(t))^{\Delta t}} - 1. \tag{30}$$

When *fixed-option* is enabled for the savings rate, then eq. (27) is generally preferred; eq. (28) otherwise. A detailed explanation for this approximation and an estimation of its magnitude are provided in Supplementary Material B. In addition to that, Figure S4 in Supplementary Material C shows a qualitative comparison of the two specifications under indicative model conditions.

2.7.1 Burke et al. (2015) specification

The regional temperature patterns (obtained as described in Section 2.5) allowed us to integrate an impact function based on Burke et al. (2015), who find an inverse U-shaped relationship between economic growth and average annual temperatures across countries and over time. Their contribution, grounded on fifty years of data across a large set of countries, estimates a global quadratic relationship for both temperature and precipitation (I concentrated on the former, as it is easier to work with and has less uncertainty). They estimate distributed lag models with 1–5 lags of a quadratic temperature polynomial to explore the persistence of temperature effects. They obtain, as base-case, the following function of growth effects, solely related to the country-level temperature variable $T_i(t)$:

$$\mathrm{h}(T_i(t)) = 0.0127 \cdot T_i(t) - 0.0005 \cdot T_i(t)^2. \tag{31}$$

Impacts on the production growth rate $\delta_{i,\mathrm{BHM}}(t)$ are then obtained by computing the difference between the result of eq. (29) at time t and its base-value under *reference* temperatures T_{i0} (defined as the average values between 1980 and 2010):

$$\delta_{i,\mathrm{BHM}}(t) = \mathrm{h}(T_i(t)) - \mathrm{h}(T_{i0}). \tag{32}$$

I included four major BHM specifications for the eq. (29) coefficients. They include different lags assumptions – capturing either short-run (SR) or long-run (LR) effects – and whether a differentiation between rich and poor countries (i.e., countries whose GDP per-capita [PPP] is respectively higher or lower than the overall median in the base year) is considered. All these coefficients are reported in Table 2.

Table 2: Specifications' coefficients for BHM impacts.

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

Last, BHM also estimate their function separately for the first half and for the second half of the data, finding no statistical difference in the mean temperature response. They conclude there is no evidence of adaptation that should be incorporated into projections of the future effects of climate change.

2.7.2 Dell, Jones, and Olken (2012) specification

Another specification I implemented in RICE50+ comes from the contribution by Dell et al. (2012) – hereafter DJO – who provide a different and forerunner empirical estimation for regional impacts. The authors assessed a linear relationship between local temperature and economic growth. Impacts on the production growth rate are obtained based on a general effect (almost irrelevant), and a more significant negative effect of an additional 1.655 percentage point reductions for poor countries only (defined as in the former BHM-differentiated case):

$$\begin{aligned}\delta_{i,\mathrm{DJO}}(t) = \quad & 0.00261 \cdot (T_i(t) - T_{i0}) \\ & - 0.01655 \cdot (T_i(t) - T_{i0})\big|_{\mathrm{GDP}_{\mathbf{CAP},i}(t_0) < \mathrm{Median}\left(\mathrm{GDP}_{\mathbf{CAP},i}(t_0)\right)}.\end{aligned} \tag{33}$$

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

2.7.3 Kahn et al. (2019) specification

I implemented a third empirical-based contribution by Kahn et al. (2019), who similarly estimated a linear relationship between local temperature and economic growth related to deviations of the country-level temperatures over the historical norm. Their main results point out that a temperature increase by one degree leads to 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 did not find a significant differentiated response between rich and poor countries. I used their main specification (that accounts for a 30-years interval) to compute the historical norm as a moving average (starting from 1980-2010, consistent with the case of Burke et al., 2015). I hence obtained the following specification for the growth effect $\delta_{i,\text{Kahn}}(t)$:

$$\begin{aligned}\delta_{i,\text{Kahn}}(t) = &-0.0586\left(\left[T_i(t)-\overline{T}_i(t-1)\right]-\left[T_i(t-1)-\overline{T}_i(t-2)\right]\right)|_{T_i(t)>\overline{T}_i(t-1)} \\ &-0.0520\left(\left[T_i(t)-\overline{T}_i(t-1)\right]-\left[T_i(t-1)-\overline{T}_i(t-2)\right]\right)|_{T_i(t)<\overline{T}_i(t-1)}\end{aligned} \tag{34}$$

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).

2.7.4 Long-run impacts bounding

Cumulative growth effects resulting from the described impact functions can lead, in very few specific countries (i.e., those with the coldest reference temperature), to extreme values in GDP production along the three-centuries execution period (cf. Figure S5 in Supplementary Material C). As a notable example, a very cold country like Finland, under the BHM-SR impact specification and a non-cooperative policy scenario, may gain up to +384% of baseline GDP value by 2100 (consistent with its projections in Burke et al., 2005). In 2200 Finland positive impacts raise to more than +20000% and increase even further afterwards.

To dampen this evident degenerating trend and therefore minimize the risk of biasing model optimal outputs, I decided to impose a maximum bound to regional impacts magnitude. I opted for a reasonable compromise of capping GDP impacts within the $[+100\%,-100\%)$ interval over no-climate-change baseline (cf. Figure S5b in Supplementary Material C). Alternative approaches demonstrated to be inadequate. A decay effect, for example, would insufficiently smooth out the magnitude of these few extreme trends (cf. Figure S5c in Supplementary Material C), with the drawback of introducing an arbitrary (and more substantial) influence to all the other countries.

2.8 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 obtained optimizing mitigation strategy for each country while taking others' behavior as given. It uses an iterative algorithm that converges to the open-loop Nash equilibrium. On the other hand, the cooperative is modelled as equivalent to there being a global social planner, which maximizes a utility function aggregating the welfare of all regions.

As in the original DICE/RICE formulations, the RICE50+ model optimizes the flow of generalized consumption over time. It assumes that regions maximize the following social welfare function:

$$W=\sum_n\sum_t\left[w(t,n)\cdot L(t,n)\cdot\left(\frac{1}{1-\eta}\cdot\left(\left(\frac{C(t,n)}{L(t,n)}\right)^{1-\eta}-1\right)-1\right)\cdot(1+\rho)^{-t}\right]. \tag{35}$$

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

RICE model uses Negishi weights (i.e., welfare weights equal to the inverse of the marginal utilities of consumption, as described by Nordhaus & Yang, 1996) for $w(t,n)$, but their distortion of inter-temporal preferences has been criticized and their implications are at odds with welfare economics (e.g., see Stanton, 2010). In RICE50+ I've therefore implemented a welfare function which disentangles preferences over inter-temporal discount ρ (as in original formulation) and regional inequality aversion γ:

$$W=\sum_{t=1}^{T}\left[\frac{1}{1-\eta}\left(\sum_n w_{\text{pop}}\,(t,n)\left(\frac{C(t,n)}{L(t,n)}\right)^{1-\gamma}\right)^{\frac{1-\eta}{1-\gamma}}-1\right]\cdot(1+\rho)^{-t}, \tag{36}$$

with population-weights $w_{\text{pop}}(t,n)=L(t,n)/(\sum_n L\,(t,n))$ and $\gamma\neq 1$ condition. Parameter ρ is set to 1.5% in the 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; 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 & Brandolini (2010) consider γ values between 0.2 and 2.5 as defensible (see also Berger & Emmerling, 2017; Emmerling et al., 2016). For the default specification I chose an intermediate value of $\gamma=0.5$, close to the value found by Tol (2010) and values used by the U. S. Census Bureau (2000). Table 3 shows the four main reference levels for γ tested in the model.

Table 3: Inequality aversion main reference levels.

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, ($\gamma > \eta$)

3. Illustrative results

In this section, I conclude the model description showing some representative results of the benefit-cost outputs. Runs include all the socio-economic baselines (SSP1-SSP5) and the climate-impact specifications described. They also account for all the four levels of inequality aversion (γ) from Table 3; note that this covers the full range suggested by Atkinson & Brandolini (2010). I also explored three different values for the utility discount rate ρ over the 0.1% - 3% interval. Cooperation and non-cooperation execution modes are both considered.

Figure 2 shows the primary globally aggregated outcomes. Panel (a) shows optimal projections for world emissions trajectories, with colors depicting cooperation and inequality aversion levels. Thicker lines highlight a representative intermediate reference scenario: SSP2 baseline, BHM-SR impacts and 1.5% utility discount rate. Projections show that non-cooperative outputs have significantly lower emissions than no-climate-change Business-As-Usual (BAU). They also visibly display the largest uncertainty range, suggesting a strong correlation with scenario definition. On the contrary, with cooperation, only inequality neutrality ($\gamma = 0$) presents significant uncertainty. From $\gamma = 0.5$ to higher values, all projections indicate the needing for fast and firm mitigation, with some negative emissions reached in the second half of the century. Panel (b) shows optimal Global Mean Temperature (GMT) increase distributions associated with these scenarios. They consistently follow the emissions trajectory patterns, reflecting both ranges and ultimate target ambition.

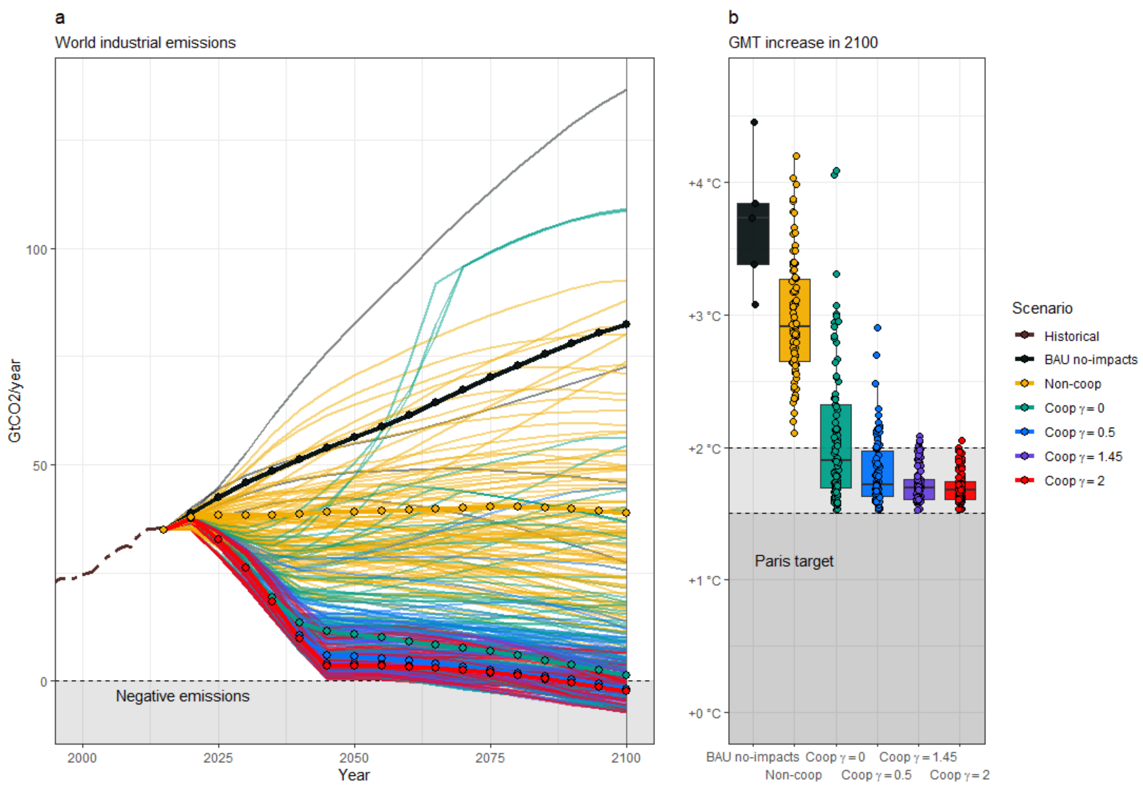

Figure 2: Benefit-cost optimal world-aggregated emissions projections (a) and 2100 Global Mean Temperature (GMT) increase distribution (b). Colors distinguish among progressively increasing cooperation and inequality aversion. Results include all impact specifications, discount rates, and SSPs baselines. Thicker lines highlight projections for a representative intermediate SSP2 reference, with BHM-SR impacts and 1.5% utility discount rate.

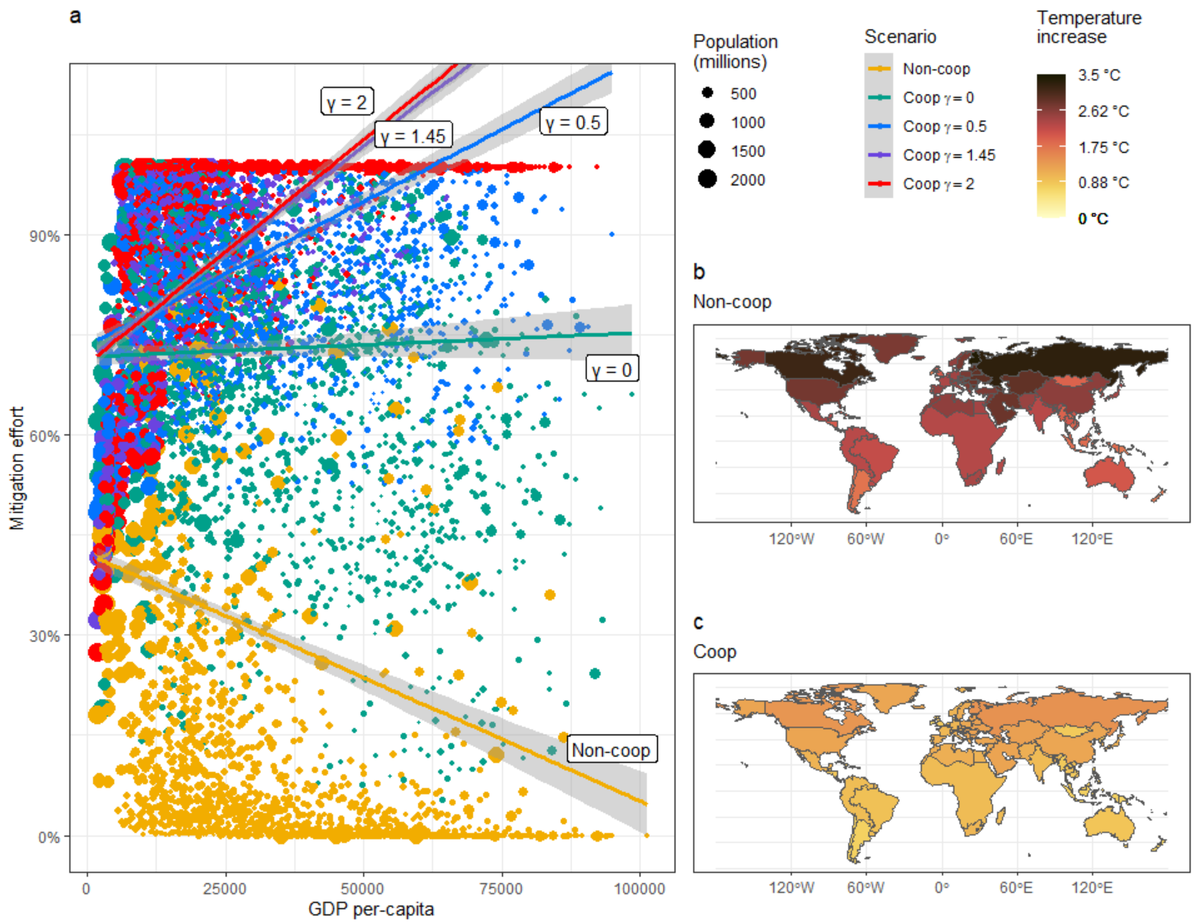

Figure 3: Panel (a) reports 2050 regions mitigation efforts over their GDP per-capita for all scenarios tested. Colors and population-weighted regression lines show the ultimate effect of cooperation and inequality aversion in the model. Panel (b) and (c) show local population-weighted average temperature increase in 2100 under non-cooperation and cooperation cases. Baseline scenario is SSP2 with intermediate values for utility discount rate and inequality aversion.

The effect of inequality aversion in the model is well depicted by Figure 3, panel (a). Here mitigative efforts from all scenarios (reported as reduction percentages of baseline emissions) are associated with the GDP per-capita for each region, for the year 2050. Point size accounts for regions' populations, while colors indicate non-cooperation or cooperation with increasing inequality aversion. As evidenced by population-weighted linear regressions, the higher the cooperation and inequality-concern, the less the burden left to the poorest, high-populated states (those hit by the strongest climate impacts). However, while on one side I see inequality aversion triggering a true concern from the richest regions, I also notice a saturating effect, since values higher than 1.45 don't vary the result significantly. The substantial effects of cooperation are also visible at a regional scale in Figures 3b and 3c. Here, I reported local population-weighted temperature-increase projections for the year 2100, which show a significant reduction under cooperation.

Figure 4 depicts residual damages distribution in 2100, under the SSP2 baseline and a 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 scenarios' patterns. Under DJO, a marked difference between the two groups persists, while Kahn specification leads to generalized negative impacts, as all the countries deviate from their historical norm.

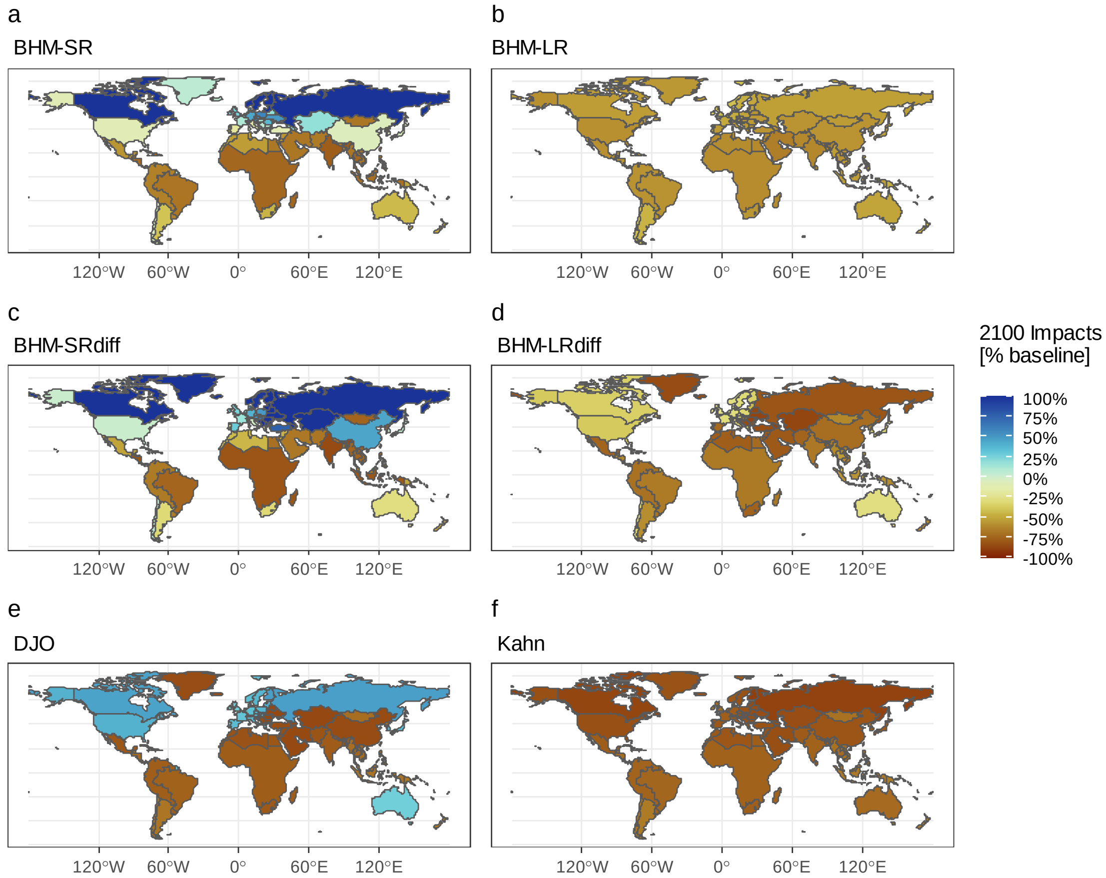

Figure 4: Impacts distribution in 2100 for each implemented specification under the SSP2 baseline and an intermediate utility discount rate. Only non-cooperative (most severe) scenarios are reported.

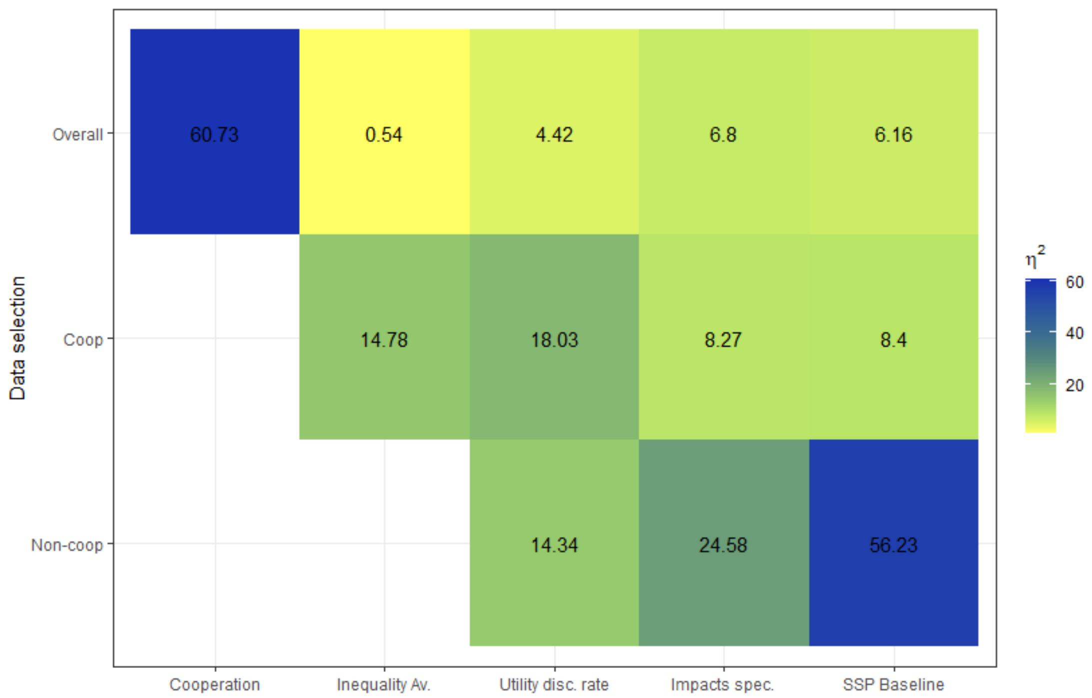

Figure 5: Uncertainty drivers associated with global mean temperature (GMT) increase projected in 2100. For each of three major categories (Overall, Coop. only, Non-coop. only) the correlation ratio (η^2) expresses a percentage measure of drivers' importance to the final GMT outcome. The eta-squared correlation ratio, according to the law of total variance, does not require the input variables to be independent or identically distributed.

Last, Figure 5 shows a sensitivity heatmap with the estimated importance of model drivers in determining GMT increase in 2100. For each of the 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. The eta-squared correlation ratio, according to the law of total variance, does not require the input 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, I observe how the *Non-coop* scenarios (third row) are largely driven by the socio-economic baselines, followed by the impacts specifications and, last, 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.

4. Conclusions

In this paper, I presented RICE50+, an extension of Nordhaus' RICE/DICE Integrated Assessment Models, featuring the noteworthy granularity of 57 independently deciding regions. I extensively described all the introduced novelties: the calibrations of local economic projections, mitigation costs, climate and temperatures downscaling process; the direct implementation of impact functions based on recent empirical findings; last, the alternative solving options for cooperation and inequality aversion. Some illustrative results confirmed that the added regional detail plays an extensive role in benefit-cost outcomes. Moreover, results suggest also that the degree of inequality aversion has a significant impact on both the global emissions pathway and the regional distribution of mitigation efforts. Last, it is also worth pointing out how this implicitly demonstrated the solving feasibility for optimizations with such a disaggregated detail level. In fact, IAMs complexity may rapidly escalate, turning fast to unbearable solving times. CONOPT solver converges and finds optimal policies in less than 30 minutes when RICE50+ is run on a commercial laptop.

Several future developments and improvements have already been identified at this stage. Among these, the noteworthiest are: (1) the definition of time-varying coalitions, which mix cooperative (within coalitions) and non-cooperative (between coalitions) behaviors; (2) the introduction of explicit adaptation decisions (currently missing), which can reduce the local impact effect with some costs; (3) a better representation of endogenous spillovers from technological changes; and (4) the introduction of potential geoengineering leverages like Solar Radiation Management and Direct Air Capturing. The automatized process which performs all described calibrations can be reused and readjusted to integrate any future data-source update or findings.

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