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To cite this article: Luca Ferrari *et al* 2022 *Environ. Res. Lett.* **17** 084029

ENVIRONMENTAL RESEARCH
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OPEN ACCESS

RECEIVED
17 June 2022

REVISED
19 July 2022

ACCEPTED FOR PUBLICATION
26 July 2022

PUBLISHED
2 August 2022

LETTER

From optimal to robust climate strategies: expanding integrated assessment model ensembles to manage economic, social, and environmental objectives

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Keywords: integrated assessment model, climate policy, deep uncertainty, multi-objective decision making, inequality

Abstract

Cost-benefit integrated assessment models generate welfare-maximizing mitigation pathways under a set of assumptions to deal with deep uncertainty in future scenarios. These assumptions include socio-economic projections, the magnitude and dynamics of climate impacts on the economy, and physical climate response. As models explore the uncertainty space within the boundaries of their objective functions, they risk providing scenarios which are too narrow and not sufficiently robust. Here, we apply robust and multi-objective decision-making methods to extract relevant information from a large ensemble of optimal emissions-reduction pathways generated by a regionalized cost-benefit integrated assessment model under deterministic welfare optimization. We show that shifting the focus from optimal to robust solutions reduces the uncertainty in mitigation strategies and aligns them toward the Paris goals. Moreover, we analyze the trade-offs between climatic (temperature), social (inequality) and economic (welfare) objectives and illustrate four robust pathways under various decision-making criteria. We show that robust mitigation strategies can lead to regional emission-reduction strategies which are fair. Our results show how to extract more comprehensive climate strategies from available scenario ensembles and that the highest discrepancies at the local level policies are found in the developing and most-impacted regions.

1. Introduction

Integrated assessment models (IAMs) couple the economy with a compact representation of the climate to explore how different sources of greenhouse gas (GHG) emissions affect climate dynamics. They investigate potential future trajectories of human and natural systems to develop insights on climate policy efficacy and implications (Weyant *et al* 1995). In particular, cost-benefit (CB) IAMs, which provide an aggregated representation of both mitigation costs and climate impacts (Weyant 2017), have been extensively applied for: (a) evaluating optimal trajectories of GHG emissions and the optimal prices they should be charged for a pigouvian tax, (b) assessing costs and benefits of non-optimal climate policies, and (c) computing the social cost of carbon (SCC), i.e. the economic damage caused by each additional ton of carbon dioxide released in the atmosphere (Weyant 2014, 2017). Some among the most-popular CB IAMs are DICE (Nordhaus 1993), RICE (Nordhaus and Yang 1996), PAGE (Hope *et al* 1993), and FUND (Anthoff 2009). Recent updates to CB IAMs have shown that the target set by the Paris Agreement (UNFCCC 2015) (i.e. limiting global mean temperature increase to well-below 2 °C and aiming at 1.5 °C) is optimal according to a benefit-cost assessment, providing quantitative support for these warming levels under a welfare economics perspective (Burke *et al* 2018, Ueckerdt *et al* 2019, Glanemann *et al* 2020, Hänsel *et al* 2020, Gazzotti *et al* 2021, van der Wijst *et al* 2021). Yet, these models belong to the realm of post-normal science (Funtowicz and Ravetz 1993) where both system's uncertainties, including value uncertainty, and stakes are high. The deep uncertainty within the socio-economic projections and the modeling of climate impacts on the economy has also cast legitimate doubts on the ultimate usefulness of these models for policy support (e.g. see Pindyck 2013, 2017).

Quantification of future climate impacts to the economy is a first and widely debated source of uncertainty. Several different types of functions linking global temperature to reductions in economic output have been estimated using expert elicitation (Nordhaus 1994, Weitzman 2012, Howard and Sterner 2017). Empirical functions estimated through econometric methods have also been increasingly implemented in IAMs. Linear income-dependent relationships between regional temperature and economic growth have been found (Dell *et al* 2012) and included in DICE showing that the gross domestic product (GDP) growth in poor regions decreases even under optimistic adaptation assumptions (Moore and Diaz 2015). Similarly, nonlinear relationships have been estimated (Burke *et al* 2015) and used to confirm the optimality of the 2 °C target (Glanemann *et al* 2020) and the persistence of income inequality resulting even after economically optimal emissions reductions (Gazzotti *et al* 2021). Moreover, Kahn *et al* (2021), proposed a linear relationship between the GDP growth rate and the changes in the country-level temperature with respect to the moving window average over the preceding 30 years. Due to the large number of approaches available in the scientific literature, estimates of climate impacts to the global economy range from 0% to −10.2% of GDP for a temperature increases of 1 °C–6 °C and between −4.9% and −99% of GDP for temperature increases of 3 °C–12 °C (Howard and Sterner 2017).

Inequality is another fundamental implication of climate impacts and it has been thoroughly examined in the literature (Dell *et al* 2012, Burke *et al* 2015, Diffenbaugh and Burke 2019, Kahn *et al* 2021, Taconet *et al* 2020). Growing evidence shows that: (a) the impacts affecting the poverty-stricken are higher than the impacts on the average population (Hallegatte and Rozenberg 2017), (b) developing countries will suffer the largest bulk of the damage (Mendelsohn *et al* 2006), and (c) climate change worsens existing inequalities (Hallegatte and Rozenberg 2017, King and Harrington 2018). In particular, Diffenbaugh and Burke (2019) show that climate change has already increased between-country inequality. Future impacts will exacerbate this issue as shown by Taconet *et al* (2020). Some IAMs have been specifically designed to evaluate the inequality resulting from optimal mitigation policies. Dennig *et al* (2015) use NICE, a modified version of RICE which divides the regions into population quintiles and calculates quintile distributions of income, showing that modeling the uneven within-country distribution of impacts is relevant to assess the vulnerability of the poorest portions of society. Gazzotti *et al* (2021) also examines between-countries inequalities, using the RICE50+ model which accounts for geographic heterogeneity describing 57 independent regions and assesses climate impacts differentiating between rich and poor regions. Their results show that even following economically optimal mitigation policies complying with the Paris Agreement, climate change impacts increase inequalities, and this effect can only be partially reduced by mitigation, even in optimistic scenarios considering cooperation and high inequality aversion.

Both climate impacts and inequality are tied to the uncertainty associated with socio-economic projections (Taconet *et al* 2020), usually explored through the shared socio-economic pathways (SSPs) narratives (Drouet and Emmerling 2016, Riahi *et al* 2017) or via Monte-Carlo sampling coupled with scenario discovery (Morris *et al* 2022).

Similarly, the value of some physical climate parameters, crucial in determining the future evolution of temperature, is not precisely bounded. Among these, the equilibrium climate sensitivity (ECS) is the most important. Even though there has been a reduction in its uncertainty ranges over the last years and, in particular, in the last IPCC report (Sherwood *et al* 2020, Forster *et al* 2021), it can lead to very different climate futures for the same emissions pathway. The scientific community has tried to shift the focus from its precise estimate toward potential solutions that adjust climate policy over time through progressive learning (Allen and Frame 2007, Felgenhauer and De Bruin 2009, Ekholm 2018).

Stochastic optimization methods have been implemented in IAMs (Jensen and Traeger 2014, Lontzek *et al* 2015, Cai *et al* 2016, Lemoine and Rudik 2017, Nordhaus 2018, Cai and Lontzek 2019, Daniel *et al* 2019, Kellett *et al* 2019, Rudik 2020) to deal with the uncertainty stemming from the several assumptions needed to project both socio-economic and environmental systems decades into the future (Ackerman *et al* 2010, Butler *et al* 2014, Gillingham *et al* 2018). Yet, these usually depend on the availability of probabilistic information whose absence is an additional challenge for decision-making (Lempert *et al* 2009, Weyant 2017, Workman *et al* 2021, Tavoni and Valente 2022).

In this context, methods have been developed to assist policy-makers based on the key concepts of adaptive decision-making and robustness (Haasnoot *et al* 2013, Marchau *et al* 2019). The potential advantages of applying these methods with respect to traditional decision-making support in the climate policy domain are well recognized in the literature (Lempert and Schlesinger 2001). A policy can be defined as robust when its performance is insensible to changes in future conditions, (i.e. future states of the world). One of the most widely used methods is Robust Decision-Making (Lempert *et al* 2006, 2009), which iteratively produces robust strategies based on information on the states of the world where the policies perform poorly. This and similar methods have been applied successfully in the climate policy domain (Hall *et al* 2012, McInerney *et al* 2012, Rozenberg *et al* 2014, Lamontagne *et al* 2019).

Methods for decision-making under deep uncertainty provide also a useful framework for integrating the different perspectives of a complex problem (Kasprzyk *et al* 2013, Maier *et al* 2016). In fact, behind the formulation of the welfare, the metric traditionally optimized in CB IAMs, many other objectives tend to remain hidden. Its implicit aggregation of preferences might shadow potential interesting compromise solutions and important trade-offs between distinct policy intentions (Garner *et al* 2016, Lempert 2021). Indeed, objectives explicitly addressing climatic and social concerns (Okereke and Coventry 2016) should also be included for a fair and just climate policy design (Sterner *et al* 2019). Multi-dimensional and in particular multi-objective decision-making schemes are therefore crucial to ensure that climate policy can robustly warrant success across the economic, social, and environmental dimensions of the climate issue (Garner *et al* 2016, Marangoni *et al* 2021).

In this work, we leverage the results reported by Gazzotti *et al* (2021) and obtained from the RICE50+ model (Gazzotti 2022) to extract the most robust climate policies according to different objectives. We simulate the policies over an ensemble of 90 possible future scenarios, defined on the basis of three relevant uncertain inputs of RICE50+, namely socio-economic scenario, ECS, and climate damages specification. The performance is assessed using the three key objectives discussed above, i.e. welfare, global mean temperature increase, and between-countries income inequality. We acknowledge that the inequality and the temperature objectives are already implicitly included in the social welfare formulation. Yet, we separate these dimensions to explicitly control their performance and be less dependent on the specific formulation and parametrization of the welfare function. Additionally, these objectives are evaluated across four robustness metrics to further filter out the uncertainty. Eventually, based on this performance dataset, we extract the three policies that perform best in each single objective, and a compromise policy achieving satisfactory performance across all the metrics and objectives considered. These four emissions pathways largely reduce the cone of uncertainty around potential future optimal cooperative climate policies and they ensure to reach satisfying objectives over many uncertain scenarios. While differences at the global scale are minor, large differences between climate policies are observed at the regional level. This highlights the fact that local emissions-reduction efforts play a key role in managing trade-offs between the different objectives.

The method applied is not computationally intensive as it does not require running additional optimizations. It can be used to evaluate decisions over a wider set of uncertainties and even more objectives. Results and insights from the RICE50+ model can support the negotiation over robust emission reduction pathways and the selection of course of action to be taken in the short and medium term.

2. Methodology

We based our analysis on the optimal emissions mitigation pathways assessed by the contribution of Gazzotti *et al* (2021). The authors obtained these pathways using a cost-benefit IAM, named RICE50+, that accounts for 57 independent regions. Regions' economic representations follow the DICE model by Nordhaus (2018), where emissions reductions over time are the primary decision variable to maximize welfare. The RICE50+ model, briefly reported in section 'The RICE50+ model', accounts for substantial spatial heterogeneities in mitigation costs and climatic impacts. Indeed, the marginal abatement cost curves (MACC) are different for each region and calibrated upon local projections of detail-process model POLES (see Gazzotti 2022 for a thorough description). Likewise, the high number of regions of the model allows for an adequate adoption of empirically-estimated impact formulations, characterized by significant differences in the climate-driven effects. Emissions, indeed, enter a simple climate model that describes the carbon cycle using a three-box model, which influences, in turn, the global temperature dynamic through a two-box model. Local temperature, the direct cause of regional impacts on GDP, is eventually linked to the global atmospheric temperature using a statistical relationship on historical temperature data.

Gazzotti *et al* (2021) assessed the emission reduction pathways under the perfect foresight assumption: decisions maximize welfare for each specific scenario considered. The different optimal solutions have been produced to cover the uncertainty across different SSPs scenarios, climate-impacts specifications, normative assumptions on inter-temporal discount rate and inequality aversion, and cooperation or non-cooperation behavior among regions. Recognizing the wide range of deep uncertainty affecting the solutions proposed, we formulate the following research questions: which solutions are the most robust across all the potential scenarios? Do robust

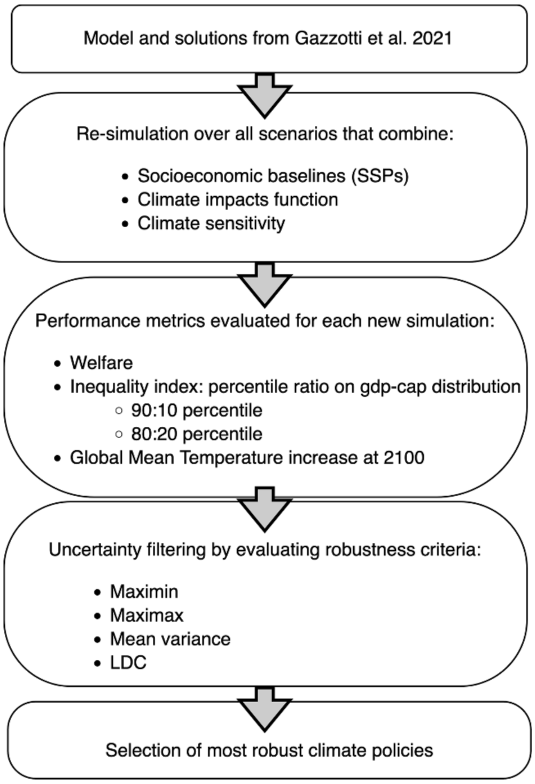

Figure 1. Methodological steps followed to carry out the robustness analysis.

policies vary significantly under different objectives targets? How do robust solutions translate from global to local scale and drive implementation of mitigation policies? To answer this question we carry out a robustness analysis of the proposed solutions to discover the most robust across different policy objectives. Figure 1 summarizes the sequence of our methodological steps.

First, we focus on the subset of cooperative solutions. Indeed, as we search for good compromise policies according also to temperature and inequality objectives, we exclude the non-cooperative outcomes since they always show worse performances for both these metrics (Gazzotti *et al* 2021). We re-evaluate all the 360 optimal mitigation pathways by Gazzotti *et al* (2021), simulating each solution across all the potential scenarios that combine: SSPs, climate impacts specifications, ECS. They comprise a total of 90 scenarios, as detailed in section 'Scenarios generation'. While we have information on the distribution of ECS, we consider the socio-economic narratives and the climate impacts specifications as deep uncertainties, since no probability can be associated with their potential outcomes. This produces a set of 32 400 new outcomes of the RICE50+ model.

For each new solution, we evaluate three meaningful performance metrics: total welfare, the global mean temperature reached in 2100 and an inequality index that accounts for per capita GDP distribution between countries. These metrics represent three among the most important (and often conflicting) objectives for future socio-economic development. For the inequality metric, we adopt two formulations for consistency with previously published publications on the matter (Diffenbaugh and Burke 2019, Gazzotti *et al* 2021).

To filter out the deep uncertainty, we employ the framework proposed by McPhail *et al* (2018). In particular, we adopt the maximin and the maximax metric (Wald 1949), and the mean-variance metric (Kwakkel and Jaxa-Rozen 2016). These three metrics represent a pessimistic, an optimistic, and a variability-averse attitude toward uncertainty respectively. We also use the LDC metric, already adopted in the literature for climate decision-making support to represent a decision-maker who deals with uncertainty by balancing average and worst-case performance (Hall *et al* 2012). These metrics are described more in detail in section 'Robustness metrics'. Previous research has shown that the choice of the decision-making criteria to deal with uncertainty matters as much as that of well-known preferences such as time discounting (Drouet *et al* 2015).

Last, we ranked solutions across each robustness criterion and each objective. Four solutions are eventually selected. For each of the three objectives, we select the solution that results in the least worst ranking across all robustness metrics. For the solution minimizing inequality, the solution was obtained by selecting the one resulting in the least worst ranking across the two formulations and all the robustness metrics. Furthermore, we propose also a compromise solution by extracting the solution which results in the least worst ranking across all metrics and objectives analyzed. The extraction process for these four climate policies is further explained in section 'Robust policies selection'.

Hereafter, these policy solutions are named after the objective they maximize, namely, *welfare*, *temperature*, and *inequality*. The compromise climate policy is intuitively labelled as *compromise*.

3. Results

In this section, we analyze the selected climate policies by examining their emission and associated temperature trajectories, their performance across different objectives and existing trade-offs, and the corresponding regional mitigation effort.

3.1. Selecting robust climate policies reduces uncertainty

Figure 2 shows the industrial emissions over time (a) and temperature trajectories (b), comparing the original set of solutions by Gazzotti *et al* (2021) with the bundle of the selected robust climate policies across all potential scenarios.

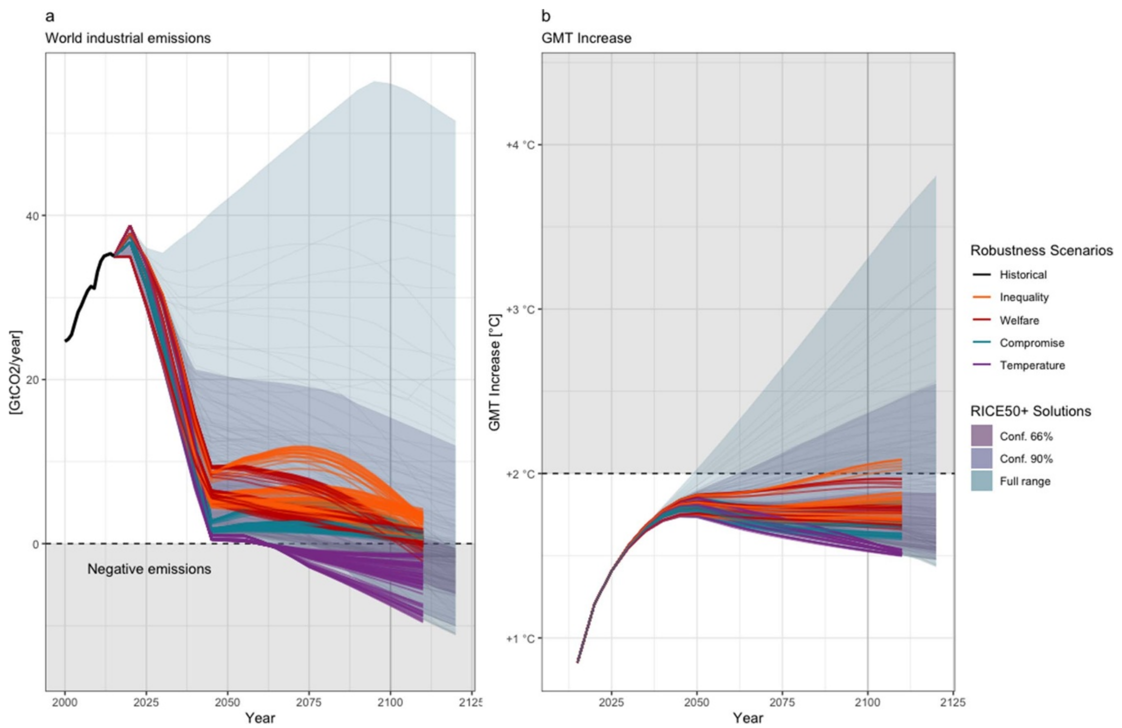

Figure 2. World industrial emissions (a) and global mean temperature increase (GMT) trajectories (b) of the selected robust climate policies. Original RICE50+ cooperative-solutions ranges are also reported for a direct comparison. Light grey lines show individual solutions, while light-blue, dark-blue and purple shadings depict their full range, their centered 90% and 66% confidence probability intervals respectively.

We see that emissions rapidly decline for all the selected robust policies, regardless of the objective considered, that is, also when focusing only on economic or inequality targets. As expected, being robust to the temperature objective implies emissions decline the fastest, while for welfare and inequality the trajectories change after 2050. The solution robust to inequality permits slightly more emissions in the second half of the century. The compromise solution, on the other hand, goes to zero more rapidly than the welfare and inequality solution. After 2050, it stabilizes until the end of the century.

As we reduce uncertainty in emission trajectories, we observe a substantial contraction in the range of potential values when moving from economically optimal climate policies to widely robust climate policies. In particular, we note how all robust climate policies remain below 2 °C in 2100, with few exceptions for the solutions robust to the inequality objective. However, this solution remains below the 2 °C threshold set by the Paris Agreement in most of the scenarios. Therefore, we can state that achieving the 2 °C temperature goal is robust for all the considered objectives.

3.2. Robustness metrics define the magnitude of trade-offs between objectives

While the emission pathways for the selected climate policies look comparable, especially until 2050, they diversify in their performances for each of the objectives examined. Figure 3 shows the ranking of selected solutions for each objective under the different robustness metrics.

We first comment on performances regarding the *maximin* robustness criteria, the one we used to select the robust climate policies. The temperature solution performs best in its primary objective but ranks low in welfare and inequality indicators. This shows how hard the reconciliation of robust performances in temperature and good outcomes for welfare and inequality is. Similarly, emission pathways robust to inequality and welfare worsen the *temperature* objective, showing modest conflicts among each other. The *compromise* policy shows an intermediate ranking across all of the objectives, showing well-balanced robustness.

Let us now consider other robustness metrics. The ranking of solutions for the temperature objective is not sensitive to changes in the robustness criterion. This is not surprising, since the cumulative emissions of every pathway are directly related to the level of warming. On the other hand, it is noteworthy to observe that the compromise policy may slightly outperform the inequality and welfare solutions in their target objectives under different robustness metrics. This highlights how the compromise solution, while minimizing the worst ranking across all the objectives and metrics, may show good performance also in welfare and inequality. Moreover, we can also see that welfare and inequality objectives are more sensitive to

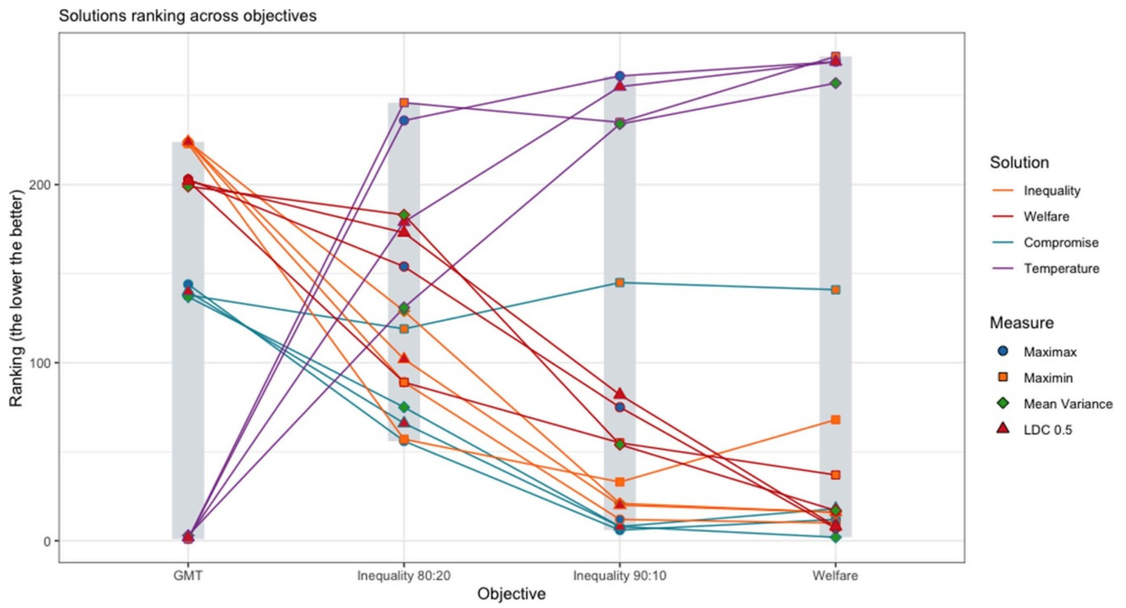

Figure 3. Ranking of the four selected robust climate policies according to the three objectives (with two indicators for inequality) and the four most important robustness metrics out of the seven considered.

changes in the robustness criterion. Indeed, exogenous factors such as the SSP storyline and the climatic impacts specification, play a crucial role in determining welfare and inequality outcomes. In turn, this leads to significant variations when adopting different attitudes toward uncertainty.

The solutions generally exhibit a strong trade-off between temperature and all the remaining objectives, while inequality and welfare show lower differences in their robustness ranking. The trade-off between the economic and the temperature objectives can be traced back to the formulation and parametrization of the welfare function. Indeed, it tends to favor consumption in the short term and be negatively affected by the costs of early stringent mitigation, essential to achieve a robust outcome for the temperature objective. Furthermore, since high-income countries always become carbon-neutral around 2050, the additional effort to get a high-ranking temperature outcome has to be borne by developing regions. This inevitably exacerbates cross-countries inequality as a direct consequence.

3.3. The potential of effort allocation in improving robustness across multiple objectives

We now examine the regional detail of the four selected robust climate policies. Figures 4 and 5 show the emission control rate in 2050 and 2080 respectively, for the four policy solutions.

In the year 2050 and under the *compromise* policy, all developed countries reach net-zero emissions (figure 4(b)), which is in line with carbon neutrality goals announced in recent years. Several developing regions in South America and South-East Asia have also reached carbon neutrality by this year. On the other hand, sub-Saharan Africa, Central America, the Middle East and parts of South Asia have not reached the net-zero target yet, and control between 60% and 80% of their baseline emissions. In contrast, under both *welfare* and *inequality* policies (figures 4(a) and (d) respectively) numerous countries reduce their mitigation effort, and, therefore, emit more. Comparing the *welfare* with the *compromise* policy, the Mediterranean countries reduce their emissions-control efforts, with the highest difference observed in Northern Africa (−35%). Same as the Indian subcontinent (−15%), Central America (−18%), South-East Asia (−20%). On the other hand, according to the *inequality* solution, the African and Indian regions emit even more, with emissions-control efforts reduced by more than −20% compared to the compromise solution. Last, according to the *temperature* solution (figure 4(c)), all the regions play higher efforts. Sub-Saharan Africa is the only big region not reaching the net-zero target, though still cutting 70% of its baseline emissions.

With the *compromise* policy in the year 2080 (figure 5(b)), several developed countries remove carbon from the atmosphere going to net negative emissions. On the other hand, sub-Saharan Africa, Central America, the Middle East and Eastern Europe have not reached the net-zero target yet, with sub-Saharan registering the lowest emission control rate (73%). Differences in emissions trajectories among different policy solutions are now less marked than in 2050. However, a similar pattern can still be observed. Concerning the *welfare* policy (figure 5(a)), differences in mitigation efforts stay within −10% in magnitude.

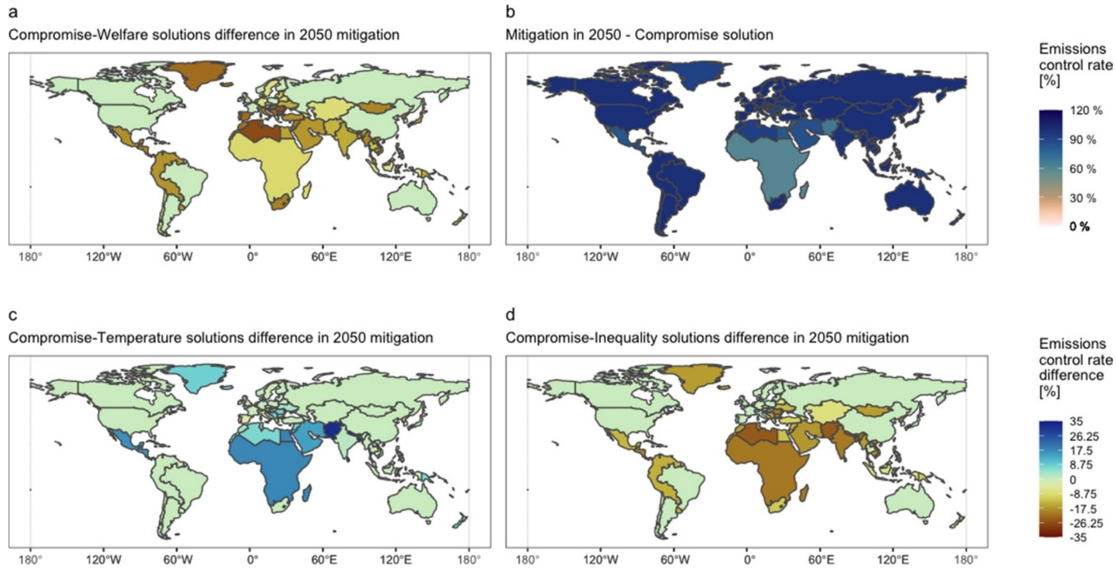

Figure 4. Panel (b) reports the values of the emissions control rate for the *compromise* solution. The difference between the emissions control rates of the *compromise* and the *temperature* solution is reported in panel (a), between the *compromise* and the *welfare* in panel (c) and between the *compromise* and the *inequality* in panel (d). All the maps are referred to the year 2050. The top colorbar shows the absolute level of emission control rate and it is associated with panel (b) only. The bottom colorbar is associated with the remaining figures and shows differences in emission control rate with respect to the compromise policy reference.

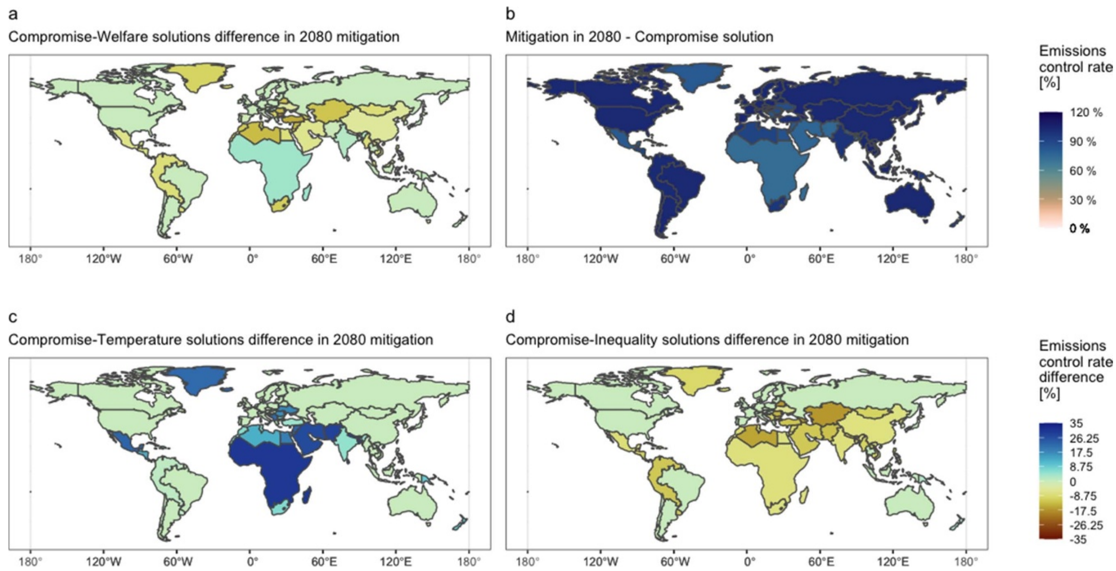

Figure 5. Panel (b) reports the values of the emissions control rate for the *compromise* solution. The difference between the emissions control rates of the *compromise* and the *temperature* solution is reported in panel (a), between the *compromise* and the *welfare* in panel (c) and between the *compromise* and the *inequality* in panel (d). All the maps are referred to the year 2080. The top colorbar shows the absolute level of emission control rate and it is associated with panel (b) only. The bottom colorbar is associated with the remaining figures and shows differences in emission control rate with respect to the compromise policy reference.

Most notably, Sub-Saharan Africa shows a slightly higher control of its emissions, trying to reduce further warming and associated climate impacts. The *inequality* policy solution (figure 5(d)) shows same pattern as in 2050, now with differences less than −15% in magnitude. This represents the only scenario that might result in a potential overshoot of the 2 °C target, as shown by figure 2. Last, figure 5(c) shows that *temperature* policy implies all regions to meet at least the net-zero target by 2080, with several developing countries already achieving a net-negative balance. As a consequence, the difference between compromise and temperature policy are more pronounced with up to +35% increases in regional emission control rates.

All the discussed figures show that similar global emission pathways may imply substantial differences at the regional scale. Changes mostly address a subset of regions, including developing countries or those that suffer the highest impacts of future climate change. Developed countries do not display significant differences and always reach the net-zero emissions target in 2050 across all the robust scenarios. Conversely, regions belonging to Africa and Asia and, to a smaller extent, Central and South America, show emissions control rates noticeably influenced by the preferred objective. Under the temperature solution, almost all countries have to fully decarbonize their economies by mid-century, whereas, under welfare and inequality solutions, more time is conceded to developing and highly-impacted regions. The compromise policy finds a general balance, with sub-Saharan Africa and tropical areas like the Middle East and Pakistan allowed to increase their mitigation efforts at a slower rate.

4. Discussion and conclusion

In the light of profound uncertainties and value-laden preferences, scenarios generated by deterministic, single-objective models are likely to not be sufficiently resilient and all-embracing. However, complex multi-objective models are computationally heavy and often simplified. Here, we showed how we can avail of existing ensembles of IAMs and expand them over a largest set of policy priorities and decision-making metrics.

Specifically, we studied the robustness of the economically optimal climate policies assessed by Gazzotti *et al* (2021) with the RICE50+ model. We simulated these policies under a broad set of different scenarios, which cover all the SSPs' socio-economic projections, different climatic impact assumptions, and a range of ECS values. We evaluate performances according to significant objectives: welfare, temperature, and between-country inequality. By applying different robustness metrics and ranking the solutions for each objective, we filtered out the uncertainty and selected four relevant climate policies: three with the least-worst ranking for each objective, and a compromise one, with the least-worst ranking across all the three objectives.

First, our results showed that performing a robustness assessment over economically optimal climate policies narrows the range of emissions and temperature pathways compared to the original ones. At the global scale, all the robust selected policies decline rapidly until 2050 and then differentiate to counterbalance the different objectives. Resulting temperature trajectories show that achieving the Paris Agreement target would be robust for all the objectives examined. To do so, policy ambitions for the next decades need to rise up to the challenge and emissions need to rapidly decline.

Second, we analyzed the trade-offs between the three objectives. Indeed, achieving low warming futures puts mitigative pressure also on the poorest countries, those that already expect to bear the highest climate impacts. It degrades their economic performance, harming both the global welfare and the inequality indicator. However, the compromise policy we selected balancing worst-case ranking across all objectives leads also to good welfare and inequality performance when a different robustness metric is considered. Policy makers should be supported in the exploration of climate policies that align different objectives as we show their advantages without departing substantially from welfare-maximizing and economically optimal solutions.

Third, although global emissions exhibit small differences across different robust solutions, the policy implications at the regional scale show a relevant diversity in the distribution of mitigation efforts. We found that the highest discrepancies involve developing countries and regions suffering the most from the damages caused by rising temperatures. Effective allocation of emissions-reduction efforts demonstrates being a complex problem as it leads to different patterns when welfare, temperature and inequality objectives are considered.

This work underlines the importance of a-posteriori robustness analyses for climate policy support to face deep uncertainty and show the trade-offs among different objectives. Although the uncertainty cannot be directly considered when assessing the economically optimal emission trajectories, it is hence reintroduced to validate solutions performance and bring the outputs of an IAM closer to the actual decision-making context. A small set of few promising alternatives can be selected by looking at their performance through robustness metrics. Furthermore, the results highlight the importance of further studies on mitigative efforts allocation. Despite a potential consensus on optimal pathways for global emissions and temperature targets, there remain strong discussion arguments at the regional scale to define a *fair* carbon-free transition.

As a final remark, note how this work does not consider other mechanisms that could potentially help to alleviate the impact of stringent mitigation objectives on inequality. Monetary transfers and other financial aid measures encouraging decarbonization in less developed countries could be an additional leverage to balance out these conflicting objectives, ensuring a fair transition toward a decarbonized economy.

Data availability statement

The data and scripts used to process data and obtain the results, along with the ones used to produce the figures are available online in the following repository https://github.com/EILab-Polimi/robustness-rice50x. The model is available in its original repository https://github.com/witch-team/RICE50xmodel and described in Gazzotti *et al* (2021) and Gazzotti (2022).

Acknowledgment

The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 821124 (NAVIGATE).

Appendix

The RICE50+ model

This study is based on the benefit-cost assessments of the RICE50+ model by Gazzotti *et al* (2021), which is based on the DICE model by Nordhaus, specifically the version DICE-2016R2 used by Nordhaus (2018). In the following sections, we will provide a brief description of the components of the model that are most relevant for our specific analyses. For more details see Gazzotti *et al* (2021).

Regional aggregation and economy

The model accounts for 57 independent regions, based on the finest regional disaggregation of the MACC available. The socio-economic drivers come from the SSP (Riahi *et al* 2017). Figure A1 shows all the 57 independent regions.

The economic representation in the RICE50+ model is largely based on the representation from Nordhaus DICE model. It computes the GDP production for each region i and time t using a Cobb–Douglas production function:

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

where $\mathrm{TFP}_i(t)$ is the total factor productivity, $K_i(t)$ the capital and $L_i(t)$ the labor. The savings rates $S_i(t)$ determine investments and capital according to:

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

and

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

In DICE they are usually left as free variables to be optimized, but in this case the savings rates have been fixed starting from historical values and converging linearly to the projections of DICE-2016R2, since the savings were not affecting the results of the optimizations in a meaningful way and were increasing the model complexity.

Emissions abatement

Every region can reduce their GHG emissions by increasing the fraction of emissions to mitigate $\mu_i(t)$, hereafter also called emission control rate. The evolution of this variable is therefore optimized by the cost-benefit analysis. It ranges between $[0, 1.2]$ and, unlike the original DICE formulation, the RICE50+ model also introduces a limitation in the mitigation increasing rate. This is set as a maximum increase of 0.2 per time step in the emission control rate of each country, based on growth rate of solar technology deployment. The marginal abatement cost is based on multiple sources to account for the spatial differences across the 57 regions considered and it is described in detail in Gazzotti (2022).

Global and local climate

The dynamics of the climate system are represented using the traditional three-box model for the carbon cycle as in the usual DICE models (Nordhaus 2018). Temperature dynamics are driven by the radiative forcing increase due to the concentration of carbon dioxide in the atmosphere, to which other GHGs are added as an exogenous component. The model used for the temperature is the two-layer model used in DICE (Nordhaus 2018), re-calibrated to match the output from the MAGICC6 climate model (Meinshausen *et al* 2011). Finally, regional temperature is obtained with a linear regression mapping global temperature anomaly to local population-weighted spatial observations to account better for the societal impact in each region. The procedure and the equation are described in detail in Gazzotti (2022).

Climate impact functions

The RICE50+ model implements the following empirically-estimated impact functions:

Burke et al *(2015) impact function*

Burke *et al* (2015) found a non-linear relationship between economic productivity and annual average temperature, with a maximum productivity at 13 °C and strongly declining at higher temperatures. Using long-run (LR) estimates and a single equation for every region, a function of growth effects related to country level temperature was obtained:

$$h(T_i(t) = 0.0127 \cdot T_i(t) - 0.0005 \cdot T_i(t)^2. \tag{A.4}$$

The impact function is hereafter called BHM. The model uses four alternative specifications, which include different time lags, capturing short-run (SR) and LR impacts, and accounting for the income differentiation between rich and poor countries. The corresponding specifications are SR-diff and LR-diff.

The impacts on the production growth rate $\delta_{i,\mathrm{BHM}}(t)$ are obtained by computing the difference between the result of equation (A.4) at time t and the

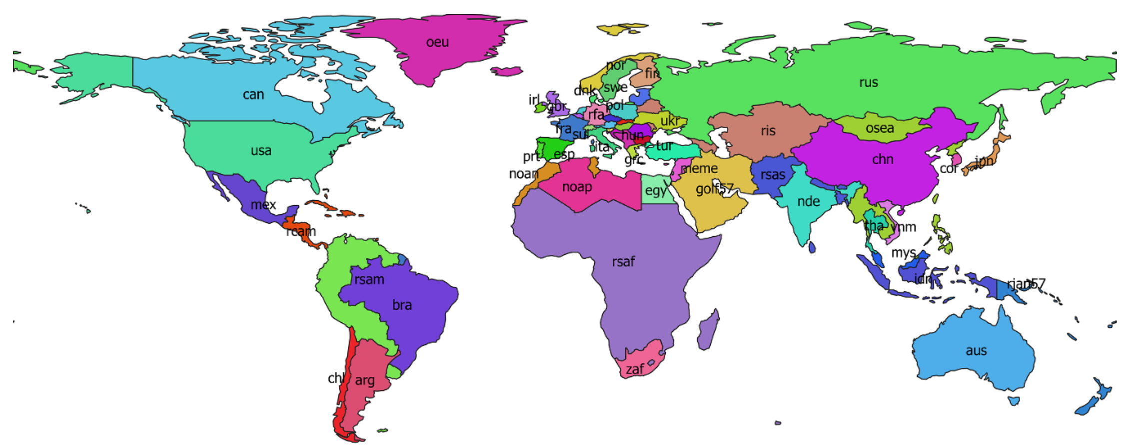

Figure A1. Geographical representation of the regions of the model.

same value under *reference temperature* T_{i0}, defined as the average values between 1980 and 2010:

$$\delta_{i,\mathrm{BHM}}(t) = h(T_i(t)) - h(T_{i0}). \tag{A.5}$$

Dell et al *(2012) impact function*

Dell *et al* (2012) provide another empirical estimation of a linear relationship between temperature and economic growth. The relationship is composed of a general, almost insignificant in magnitude, effect and a strong negative effect of growth reduction that affects only poor countries, defined as having GDP per capita below the median in the base year. The relationship is formalized as:

$$\begin{aligned}\delta_{i,\mathrm{DJO}}(t) &\\ &= 0.00261 \cdot (T_i(t) - T_{i0}) - 0.01655\\ &\quad \cdot (T_i(t)) - T_{i0})\,|_{\mathrm{GDPpc}_i(t_0) < \mathrm{Median}(\mathrm{GDPpc}_i(t_0))}.\end{aligned} \tag{A.6}$$

Kahn et al *(2021) impact function*

The last empirical estimation by Kahn *et al* (2021) provides an empirical relationship between growth rate and the changes of the country-level temperature over the historical norm. The results show a decrease of growth rate for a one degree both in temperature rising and decreasing. There is no differentiation between rich and poor countries. The relationship is:

$$\begin{aligned}\delta_{i,\mathrm{Kahn}}(t) = -0.0586 \cdot \big([T_i(t) - \overline{T}_i(t-1)]&\\ -[T_i(t-1) - \overline{T}_i(t-2)]\big)\,|_{T_i(t) > \overline{T}_i(t-1)}&\end{aligned} \tag{A.7}$$

$$\begin{aligned}-\,0.0520 \cdot \big([T_i(t) - \overline{T}_i(t-1)]&\\ -\,[T_i(t-1) - \overline{T}_i(t-2)]\big)\,|_{T_i(t) < \overline{T}_i(t-1)}&\end{aligned} \tag{A.8}$$

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

Table A1. Inequality aversion alternative values.

γ value	Interpretation
0	No inequality aversion
0.5	Intermediate inequality aversion (default)
1.45	High inequality aversion
2	Very high inequality aversion

Welfare

The RICE50+ model implements an extended welfare function with respect to the original DICE. It replicates the idea of maximizing global consumption, but it also allows to gradually change from equal marginal utility to population weighting by using a parameter of inequality aversion γ. It is defined as:

$$\begin{aligned}W = \sum_{t=1}^{T}\left[\frac{1}{1-\eta}\left(\sum_i w_{\mathrm{pop},i}(t)\left(\frac{C_i(t)}{L_i(t)}\right)^{1-\gamma}\right)^{\frac{1-\eta}{1-\gamma}} - 1\right]&\\ \cdot (1+\rho)^{-t}.&\end{aligned} \tag{A.9}$$

The model uses the four reference levels listed in table A1. The parameter ρ represents the utility discount rate, also called Pure Rate of Social Time Preference, and has a default value of 1.5%. The regions can maximize their welfare either in a non-cooperative or cooperative setting.

Scenarios generation

The reference scenario over which all the solution already found by Gazzotti *et al* (2021) are re-evaluated are built based on the uncertainty represented by the SSP scenarios, different climate impacts functions, and the climate sensitivity. For the ECS, the central value and the values at the borders of the likely interval have been used in accordance with the IPCC evaluation (Forster *et al* 2021). The drivers of uncertainty are reported in table A2.

Table A2. Drivers of uncertainty.

Driver	Values
SSP	SSP1 SSP2 SSP3 SSP4 SSP5
Impact function	BHM-SR BHM-SRdiff BHM-LR BHM-LRdiff DJO Kahn
ECS (°C)	2.5 3 4

Additional objectives

In addition to the traditional economic indicator used in cost-benefit IAMs, the social welfare obtained over the model horizon, we include two other objectives. For what concerns the environmental objective, we adopt the global mean atmospheric temperature increase measured at 2100 with respect to pre-industrial levels. As for the inequality objective we adopt a ratio of high and low percentiles derived from the global distribution of GDP per capita. We adopt the 90:10 ratio, i.e. the ratio of 90th percentile divided by the 10 percentile, and the 80:20 ratio, i.e. the 80th percentile divided by the 20th percentile. These two indicators have already been used as inequality metrics in previous studies (Diffenbaugh and Burke 2019, Gazzotti *et al* 2021). All these indicators are evaluated in the year 2100 when both the effects of climate change and climate policy will be evident for the global economy and climate.

Robustness metrics

In the following section we present the metrics adopted to examine the robustness over the set of scenarios simulated for all the policies. In particular, we refer with the letter X and S to the set of economically optimal policies and reference scenarios respectively. Additionally we refer with x_i, to each potential solution, with s_i to each reference scenario, and with $f(x_i, s_i)$, to the value of the objective function under solution x_i and in scenario s_i.

The *maximin* metric (Wald 1949) is a metric that represent a very high level of risk aversion, as it focus on the worst possible performance of every solution, also known as security level. It guarantees the selection of a solution that will have a performance at least equal to the security level. The robustness value is:

$$R_{x_i} = \min_{s_i \in S} f(x_i, s_i). \tag{A.10}$$

The *maximax* metric (Wald 1949) is a metric that represent a very high level of optimism and it is the opposite of the *maximin* metric. It focuses on the best possible performance in a solution. The robustness value is:

$$R_{x_i} = \max_{s_i \in S} f(x_i, s_i). \tag{A.11}$$

The *mean-variance* metric is based on the concept that a robust solution will have a good average result with limited dispersion around it (Kwakkel *et al* 2016). It represents an average level of risk aversion. The robustness value is formalized as follows, differentiating between the cases of performances to be maximized or minimized:

$$R_{x_i} = \begin{cases} (\mu_{x_i} + 1)/(\delta_{x_i} + 1) & \text{maximization} \\ -(\mu_{x_i} + 1)(\delta_{x_i} + 1) & \text{minimization} \end{cases} \tag{A.12}$$

where μ_{x_i} and δ_{x_i} are respectively the mean and standard deviation of the performance values $f(x_i, S)$ of solution x_i over the set of scenarios S. The unity is added to numerator and denominator of the fraction to avoid situations where μ_{x_i} or δ_{x_i} are zero. According to Kwakkel *et al* (2016), this metric has some downsides: it does not provide insights on the trade-offs between improving μ_{x_i} and reducing δ_{x_i}, functions combining μ_{x_i} and δ_{x_i} are not always monotonically increasing and it treats equally positive and negative deviations from the mean.

The limited degree of confidence (LDC) (Aaheim and Froyn 2001, McInerney *et al* 2012), a metric not discussed by the framework by McPhail *et al* (2018), is a weighted average between the worst outcome (represented by the maximin criterion) and an expected utility. However, the maximin criterion focuses on the single worst performance of a solution, ignoring other poor outcomes. For this reason, the metric we chose is an alternative formulation proposed by McInerney *et al* (2012) which replace the maximin criterion with the Conditional Value at Risk (Pflug 2000). This consists in the expected value of the worst qth portion of the performances distribution of a solution over the scenarios S. The robustness value is then calculated as:

$$R_{x_i} = \beta \left[\frac{1}{N_S} \sum_{i=1}^{N_S} f(x_i, s_i) \right] + (1 - \beta) \left[\frac{1}{qN_S} \sum_{i=1}^{qN_S} f(x_i, s_i) \right] \tag{A.13}$$

where β is the weight of the weighted average and N_S is the number of scenarios. For the implementation we selected q equal to 0.1, to consider the worst 10th portion of the performances distribution of every solution and $\beta = [0.2; 0.5; 0.7; 0.9]$.

Robust policies selection

The robustness values of each policy R_{x_i} have been used to rank the policies x_i so that the one with the best robustness value has the highest ranking, associated with a rank of 1. To select the most robust policy $x*$ according to multiple metrics, we used the maximin criterion. This allowed us to select a robust policy with a high degree of risk aversion. In the case of the single-objective solutions, this is formulated as follows:

$$x^* = \arg\max_{x_i \in X} \left[\min_{i \in M} \mathrm{Rank}_{i,\mathrm{Welfare}} \right] \tag{A.14}$$

$$M = [\text{maximin, maximax, Mean-variance,} \\ \text{LDC}(\beta = 0.2), \text{LDC}(\beta = 0.7), \text{LDC}(\beta = 0.7), \\ \text{LDC}(\beta = 0.9)] \tag{A.15}$$

$$x^* = \arg\max_{x_i \in X} \left[\min_{i \in M} \text{Rank}_{i,\text{GMT}(2100)} \right] \tag{A.16}$$

$$M = [\text{maximin, maximax, Mean-variance,} \\ \text{LDC}(\beta = 0.2), \text{LDC}(\beta = 0.7), \text{LDC}(\beta = 0.7), \\ \text{LDC}(\beta = 0.9)] \tag{A.17}$$

$$x^* = \arg\max_{x_i \in X} \left[\min_{i \in M, j \in Ineq} \text{Rank}_{i,j} \right] \tag{A.18}$$

$$M = [\text{maximin, maximax, Mean-variance,} \\ \text{LDC}(\beta = 0.2), \text{LDC}(\beta = 0.7), \text{LDC}(\beta = 0.7), \\ \text{LDC}(\beta = 0.9)] \tag{A.19}$$

$$Ineq = [\text{90:10 ratio, 80:20 ratio}] \tag{A.20}$$

where for the inequality solution we have considered the least worst ranking across all the robustness metrics and the two different formulations of the objective.

In the case of the compromise policy, the same concept has been applied also over the objectives. Therefore, the maximin criterion has been applied over the rank across metrics and objectives to derive the most robust compromise policy. This can be formulated as follows:

$$x^* = \arg\max_{x_i \in X} \left[\min_{i \in M, j \in O} \text{Rank}_{i,j} \right] \tag{A.21}$$

$$M = [\text{maximin, maximax, Mean-variance,} \\ \text{LDC}(\beta = 0.2), \text{LDC}(\beta = 0.7), \text{LDC}(\beta = 0.7), \\ \text{LDC}(\beta = 0.9)] \tag{A.22}$$

$$O = [\text{Welfare, GMT(2100), 90:10 ratio, 80:20 ratio}]. \tag{A.23}$$

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