Self-adaptive multi-objective climate policies align mitigation and adaptation strategies

Angelo Carlino
Politecnico di Milano https://orcid.org/0000-0002-8403-9070

Massimo Tavoni
Polytechnic University of Milan https://orcid.org/0000-0001-5069-4707

Andrea Castelletti (andrea.castelletti@polimi.it)
Politecnico di Milano https://orcid.org/0000-0002-7923-1498

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SELF-ADAPTIVE MULTI-OBJECTIVE CLIMATE POLICIES ALIGN MITIGATION AND ADAPTATION STRATEGIES

Angelo Carlino
Dept. of Electronics, Information and Bioengineering
Politecnico di Milano
Milano, Italy

Massimo Tavoni
Dept. of Management, Economics and Industrial Engineering
Politecnico di Milano
Milano, Italy
RFF-CMCC-EIEE, European Institute on Economics and the Environment
Milano, Italy

Andrea Castelletti
Dept. of Electronics, Information and Bioengineering
Politecnico di Milano
Milano, Italy
RFF-CMCC-EIEE, European Institute on Economics and the Environment
Milano, Italy
Institute of Environmental Engineering
ETH Zurich
Zurich, Switzerland

ABSTRACT

With intensifying climate change impacts, there is a risk that economic resources needed to adapt to the rising damages are diverted away from emission reduction, jeopardizing the chances of stabilizing temperature within safe levels. Indeed, the traditional static single-objective formulation leads to a conflict between mitigation and adaptation, invalidating the recently established consistency of cost-benefit analysis with Paris agreement targets. Here, we show that this tension can be resolved by integrating multi-objective optimization and feedback control in the DICE model to design self-adaptive climate policies trading off welfare maximization with Paris Agreement achievement. These policies allow adjusting against uncertainty as information on the socio-climatic system accumulates thus more realistically representing the policy-making process. Years above 2°C are drastically reduced, and costs of meeting the Paris agreement lowered by 2 trillion USD emphasizing the need for integrating adaptation and mitigation strategies and the value of embracing a self-adaptive and multi-objective perspective.

Main

Social and economic impacts of climate change have become increasingly studied and quantified over the last years [1, 2] and are on the rise [3, 4]. Econometric assessments rely on panel data to explain observed relationships between socio-economic and climatic variables over time and across different geographical regions using regression models [5, 6]. This methodology reveals the strong interconnections between climate trends or shocks and social and economic indicators, both at the sectoral and aggregated level [7, 8, 9, 10, 11, 12, 13, 14].
Projecting the estimated economic response to climatic variables into the future results into substantial losses for the

global economy [15, 16, 17], with estimates of average global reduction of GDP per capita in 2100 in the order of 30% with respect to a baseline high emissions scenario [6], increasing the predicted impact by one order of magnitude with respect to expert elicited damage functions used in DICE and other cost-benefit IAMs [18, 19]. Even though the debate over monetary value of future climate damages is still active, both econometric and traditional expert based formulations have been recently used to assess the economic optimality of limiting global temperature increase below 2°C [20, 21], in line with the Paris Agreement [22].

Yet, as climate impacts intensify, there is a risk that economic resources allocation shifts from mitigation to adaptation, the process of adjustment to actual or expected climate and its effects [23, 24, 25].
Given the potential societal and economic benefits of an effective implementation of adaptation strategies and the inevitable need to cope with future climatic conditions [26, 27, 28], the quest for the optimal mix of mitigation and adaptation has been a long-standing issue in climate policy [29, 30]. In order to explore the synergies and the conflicts between the two, cost-benefit IAMs, which originally describe adaptation implicitly [31], have introduced various compact form representations of its fundamental working principles [32, 33, 34, 35]. When climate policy is designed contemplating this additional lever, the transition to carbon neutrality is delayed, confirming results obtained for the energy and power sector [36, 37].
Critiques of such approaches question the lack of some essential features of adaptation: its mostly bottom-up nature, inherent handling of uncertainty as well as its rapid activation in response to sudden changes (i.e. extreme events) rather than building up alongside with climatic trends [38]. Nevertheless, more information and recommendations are required by decision makers at different scales to plan and coordinate their climate mitigation and adaptation strategies [39, 40]. To this aim, IAMs remain a useful tool to analyze and further explore the interplay between mitigation and adaptation in climate policy, especially to analyze key relationships and identify critical areas requiring further research [41, 42, 43].

Here we show that, coherently with previous scientific results on adaptation in integrated assessment modelling, the introduction of adaptation in DICE delays mitigation and jeopardizes the chance of meeting the Paris Agreement, despite increased will but in the face of limited economic and political capital, invalidating recent results on its economic optimality [21, 20, 44].

However, three fundamental issues dispute the above point and motivate a modelling shift to quantitatively address their relevance: the deterministic nature of DICE, the corresponding static design of climate policies and its single-objective characterization.
Indeed, the deep uncertainty in the modelled evolution of the coupled socio-economic and climatic systems [45, 46, 47, 48, 49, 50] calls for an adaptive decision-making approach in climate policy and integrated assessment modelling [51, 52]. In fact, static intertemporal optimization, designed to fix decisions once and for all, is not able to represent the evolution of climate policy along with changes in the state of the socio-economic and climatic system realistically; furthermore, its application over many uncertain scenarios would also result in contradictory policy recommendations [53]. For this reason, we propose self-adaptive climate policies (SACPs) to describe how climate policy decisions can change depending on the observed socio-climatic state of the system: the loop between the information available to a decision maker in a given time and its subsequent action is closed to explicitly consider uncertainty and react to new information. Adaptation also seems to be the climate policy constituent that might benefit the most from the improved decision making realism that this technique yields [54]. SACPs are based on optimal control theory, and their applications in climate policy range from stochastic and approximate dynamic programming [55, 56, 57, 58, 59, 60] to model predictive control [61, 62].
Moreover, the single-objective welfare maximization formulation of DICE cannot explain the complex and multi-faceted nature of climate policy and recent carbon neutrality plan declarations: passing the 2°C warming threshold would significantly increase the risk of catastrophic climate damages [63, 64], an undesirable outcome under a socio-political perspective [65, 66, 67]. Keeping temperature within safe levels, as recommended by the Paris Agreement, is therefore a fundamental political objective that will shape climate strategies over the next years and that should be directly considered to model the policy design process [68].

In this paper, we update a simulation version of DICE [69, 50] with the most recent improvements to the model [20]. We re-introduce explicit adaptation choices as short-term actions and long-term investments in adaptation stock [33] to assess the importance of the three points discussed above. First, we directly include uncertainty - stochastic, parametric and structural - over both the physical and the socio-economic model components, covering also key uncertain factors such as adaptation efficiency and climate damages specification. Second, to cope with the uncertain nature of the resulting model, we rely on SACPs to implement a rational agent whose decisions change in front of new evidence. Third, we design the SACPs embracing a multi-objective perspective [70] to transparently reveal the conflicts between welfare maximization and compliance with the Paris Agreement exploring the set of Pareto-optimal alternatives.
Even though the discrepancy between economic and institutional agreements comes back when introducing explicit uncertainty and adaptation in DICE, SACPs reduce the conflict. The improvement is mostly due to the ability to flex-

ibly manage adaptation options depending on the current realization of each scenario, reducing net climate damages especially in dangerous scenarios. As both net damage and adaptation costs are reduced significantly via SACPs, more economic resources are available in the short-term to increase abatement effort and keep warming within safe limits without compromising the level of welfare. This also means that, in order to robustly achieve Paris Agreement targets, costs are reduced by 2 trillion USD with respect to the traditional static climate policies. Even though the trade-off strategy that will better describe the aggregate future behavior of decision makers is unknown, we show that there will be updates and adjustments so that, even if a welfare-maximizing strategy is pursued, years above 2°C will be reduced by one third.

Resurfacing conflict

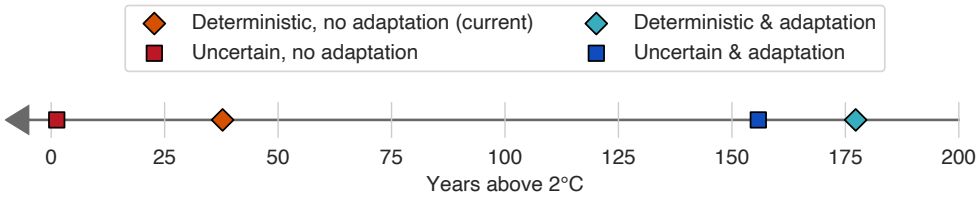

Figure 1: Implications for Paris Agreement compliance using the traditional static welfare maximization decision-making model. Uncertainty makes lower temperature economically favorable but including adaptation leads to a resurgence of the conflict between economic optimality and climate stabilization.

Explicit uncertainty and adaptation are two fundamental aspects overlooked in recent cost-benefit analysis proving the economic optimality of the Paris Agreement [21, 20]. We measure the effect of these two factors reporting the average number of years above 2°C under different modelling assumptions (see Methods) in Figure 1. A deterministic decision making model without explicit adaptation - equivalent to latest cost-benefit analysis and starting point of this analysis - results into around 35 years above 2°C in average. When adding only explicit uncertainty in the design of the policy, minimizing overshoot is also economically optimal, while when adding adaptation only, the temperature threshold is crossed for 180 years. Crucially, when both factors are accounted for, adaptation is dominant resulting in almost 160 years above the 2°C threshold: the conflict between the Paris Agreement temperature goal and welfare maximization resurfaces.

The rationale behind these temperature outcomes lies in the actions that can be considered by the decision maker to design the climate policy. Indeed, if adaptation is not explicitly available, dangerous climate impacts can only be reduced via additional mitigation, as visible in Figure S1. On the other hand, with explicit adaptation, mitigation can be postponed as adaptation reduces future impacts. Even under strong uncertainty, much higher investments in adaptation are preferred to early mitigation resulting in high emissions, high temperature and conflict with the 2°C threshold.

Conflict reduction

First, we explore the trade-offs between the objectives using multi-objective static climate policies (see Methods), in line with previous research in this direction [69]. The solution, actually a set of Pareto optimal solutions for which improving one objective leads to a degradation of the other, is reported in Figure 2 and displays the full range of alternatives solutions to the problem without a-priori aggregating the two objectives. Time spent above 2°C can be reduced by decreasing welfare: while this is not very costly when considering the solution maximizing economy, going towards zero overshooting probability requires a much higher loss in welfare.

Second, we show that, by adopting a self-adaptive multi-objective decision making model (see Methods), it is possible to reduce the conflict as the obtained Pareto front moves towards the direction of preference for both objectives (see Figure 2). In this case the solution is a set of Pareto-optimal control polices that map the current state of the socio-climatic system into the next action to be taken. This allows to change strategy and react to uncertainty based on state information - i.e. the dynamic variables which influence the evolution of the system to the next time step - where knowledge about the system accumulates as this evolves in time during each simulation. This mechanisms yields an improved representation of real decision making as our decision will inevitably adapt to the emergence of new information about the socio-climatic system. With respect to the static single objective climate policy, years above

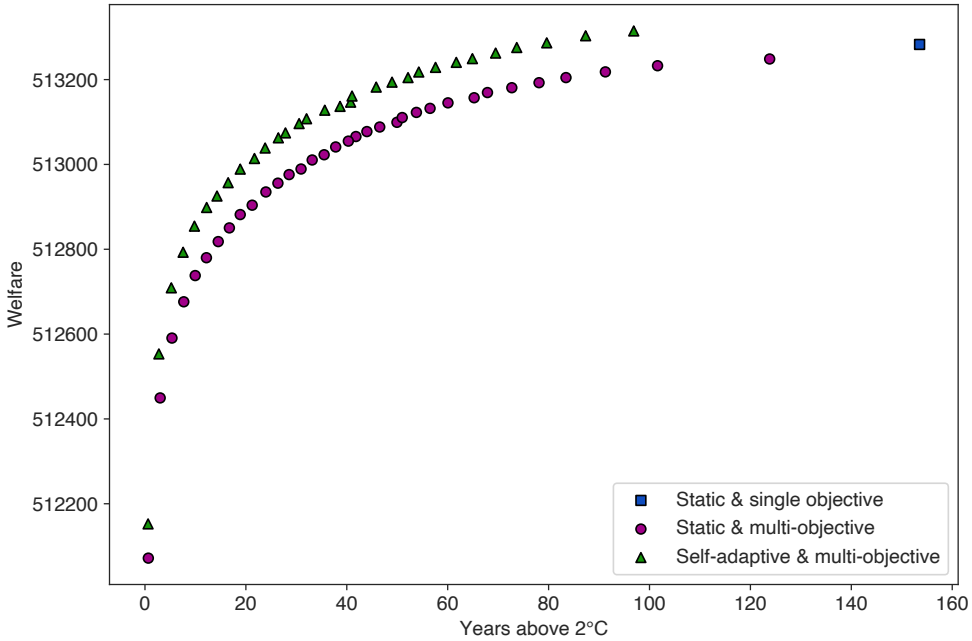

Figure 2: SACPs can largely reduce the conflict between economic and institutional perspective as the Pareto front moves in the direction of preference for both temperature and economic objectives with respect to multi-objective static climate policies. The static single objective climate policy presents a stark contrast between the two objectives and reports the worst outcome in terms of 2°C overshoot.

2°C are halved with the same level of welfare. Additionally, compared to the static multi-objective climate policies, for each level of welfare, time above the threshold is reduced by 33-50%. Analogously, for the same level of 2°C overshoot events, welfare can be improved. Most notably, also the welfare-maximizing trade-off limits the overshoot period by more than 35% with the respect to the single objective static climate policy, substantially narrowing the window of maximum future warming.

The improvements achieved with the SACPs remain, with different magnitudes, also when adopting a risk-management formulation of the economic objective, i.e. adopting the 90%, 95% and 99% conditional value at risk of welfare [71, 72]. As shown in Figure S2, the SACPs robustly dominate the static multi-objective climate policies in all cases and this further increases under higher risk aversion for low temperature strategies.

Nonetheless, the magnitude and shape of the conflict between temperature and economic objective is substantially affected by changes in social discount rate parameters, namely, the rate of social pure time preference - which is a measure of the importance of future utility for the present generation - and the elasticity of marginal utility - that measures intertemporal inequality aversion [73, 20]. Indeed, by simulating static and self-adaptive climate policies with expert-elicited values of rate of social pure time preference and elasticity of marginal utility available from previous works [73, 20], we find that climate policies favoring temperature goal can sometimes reach the highest welfare. Conversely, those maximizing welfare can result in poor economic performance depending on the social discount rate assumed, as shown in Figure S3. However, conflict between the two objectives can still be observed under many discount rate parametrizations for both static climate policies and SACP with the latter robustly achieving higher welfare for similar overshoot level. Finally, extreme climate policies, i.e. those ones favoring substantially either the economic or the temperature objective, seem to be less robust and produce the highest variability as the welfare obtained by such policies can degrade substantially under different discount rate parametrizations.

Adjusting climate policy to unfolding scenario

Self-adaptive multi-objective decision making reduces the conflict between the objectives as climate policy is adjusted to each scenario simulated and the different components of total cost are reorganized in order to achieve satisfactory performance in both objectives. In Figure 3, different cost metrics together with the defined objectives are reported

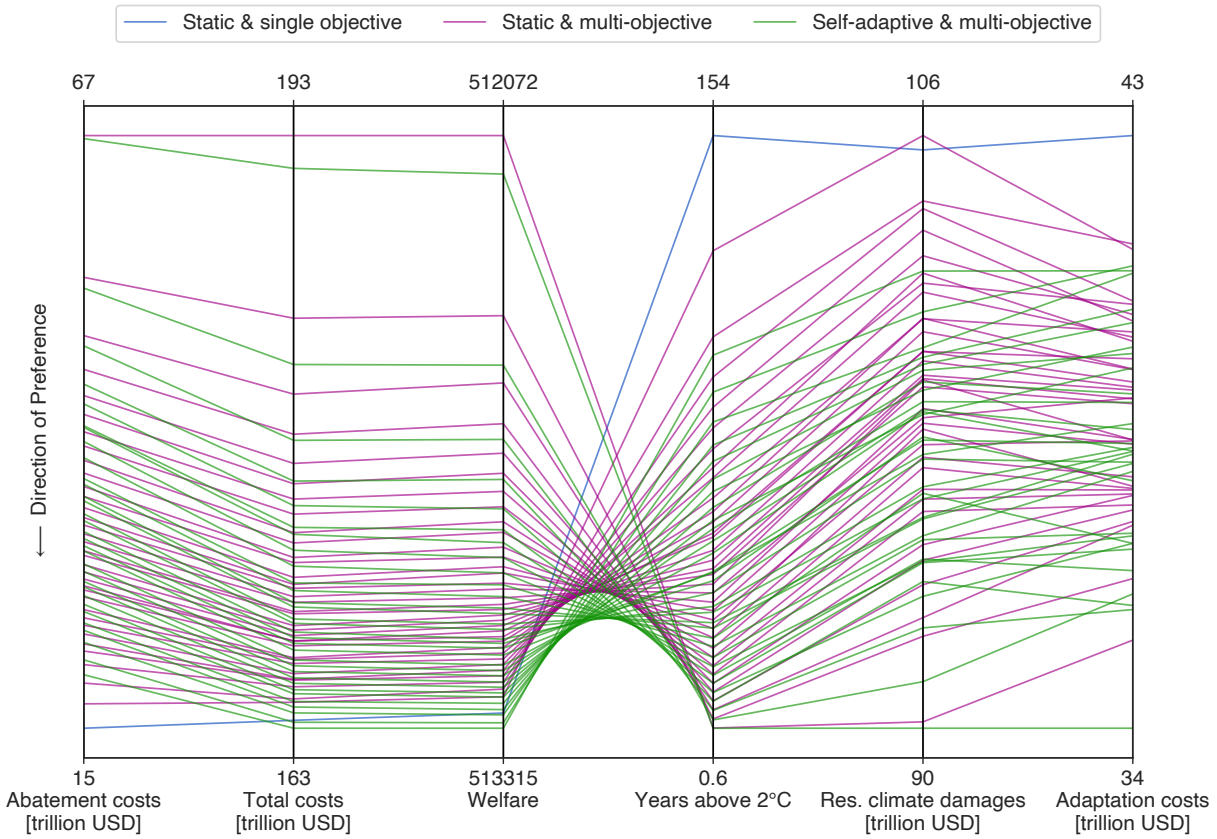

Figure 3: Models' performance with respect to different cost metrics and the two objectives considered, namely, welfare and years above 2°C. For each metric and objective considered, the preferred value lies at the bottom end of each axis. Cost metrics are reported as net present value trillion USD and are computed using Ramsey discounting.

such that our ideal solution would be represented by a line crossing all the axes at their bottom end, i.e. a line which maximizes welfare while minimizing 2°C overshoot with the lowest costs. The two central axes report the objectives: the trade-off between the two is represented by the fact that the lines intersect since improving performance in one objective leads to reduce it in the other. This conflict is strongly reduced using SACPs as corresponding lines intersect at a lower point. Furthermore, the latter have lower total costs - which correlates strongly with welfare - for any given level of abatement expenditure. In other words, for a defined emissions reduction expenditure, other costs are managed better and reduced leading to lower total costs. Also, for a given value of total costs, welfare is slightly improved. This is a consequence of the strong reduction in residual climate damages and adaptation expenditure under same 2°C overshoot occurrences via SACPs.

To better understand the role of adaptation costs, we explore their variation across climate damages specification and efficiency of adaptation measures, a critical uncertain parameter regulating the effective reduction in climate damages occurring due to adaptation measures. As reported in Figure 4 and in Figure S4-S5, while static climate policies stick to a predefined adaptation strategy, which performs well on average and produces similar costs over the different scenarios considered, SACPs display a clear ability to increase adaptation effort to either curb higher climate damages or counterbalance lower adaptation efficiency. This means that higher adaptation effort is applied when residual climate damages are high in order to better hedge against them, while less effort is needed when lower climate impacts are observed allowing for more consumption and improved welfare.

In short, using a similar amount of economic resources in adaptation, SACPs are able to modulate climate adaptation strategies for each scenario simulated, reducing residual climate damages and leading to an overall reduction in total costs. Furthermore, these savings in future adaptation costs motivate higher expenses in emissions reduction in the short term, which remains the best strategy to reduce risk of high climate damages.

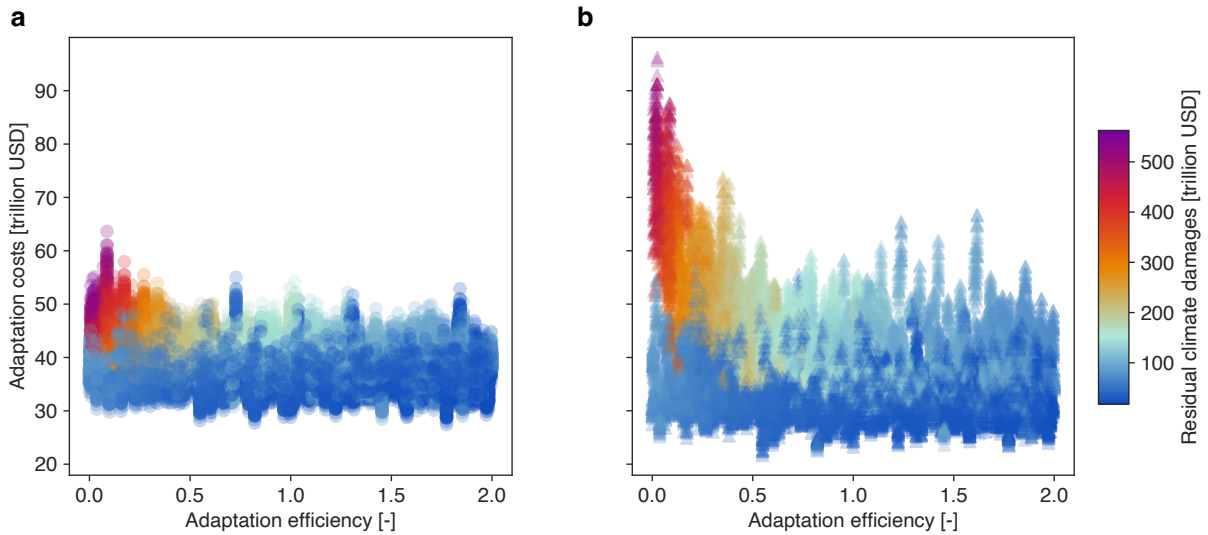

Figure 4: Adaptation costs for static (a) and self-adaptive (b) climate policies are reported against the adaptation efficiency and residual climate damages. Self-adaptive climate policies modulate the adaptation effort proportionally to residual climate damages and inversely proportional to adaptation efficiency.

Implications for social cost of carbon

The social cost of carbon (SCC) [74, 75] is the economic value of an additional metric ton of CO2 emissions and is one of the most widely studied and used option to implement emission reductions in accordance with a specific climate policy. Cost-benefit IAMs such as DICE, PAGE and FUND are used to estimate this metric [18, 76] which is still a subject of heated debate as its value remains largely uncertain [47, 77, 78, 79]. In this regards, the self-adaptive decision making model can help to better characterize and understand the inherent uncertainty to foster a more open debate also on the political connotation of this indicator.

As reported in Figure 5, under the traditional static decision making model, SCC estimates do not vary significantly with respect to a different temperature target. Both average and median values rest in the interval 40-70 USD/tCO2. Large uncertainty over the SCC remains at any temperature level and, for any given SCC estimate, any level of warming can occur, making it difficult to map one over the other, as shown in the bottom panel. On the other hand, a more clear pattern emerges with SACPs: while large uncertainty remains and for a single estimate many different temperatures can be reached, the probability of such outcomes depends strongly on the SCC. Of course, the mean and median estimate reflect this change and display a strong increase as the level of warming and years above 2°C are reduced: while for a welfare-prone policy mean and median are in the range of 50-60 USD/tCO2, the policy robustly achieving the Paris Agreement reports values around 140 USD/tCO2. This is coherent with the fact that, one additional ton of CO2 in the atmosphere can be crucial for a climate policy aiming to robustly achieve the Paris Agreement, as it would incur in much higher costs striving to pursue the predefined level of warming. On the other hand, policies which weigh economic performance more than Paris Agreement compliance, are much less impacted by one additional ton as their strategies are not fundamentally changed. Therefore, looking at the self-adaptive model histogram in the bottom panel in Figure 5, it is possible to describe the preference for a given level of warming of the decision maker, given the adopted SCC. If the latter is in the order of 50 USD/tCO2, the decision maker is much more concerned about economic performance and she implicitly accepts the risk of much higher temperature at the end of the century. On the other hand, by setting it above 125 USD/tCO2, high temperatures are almost ruled out revealing the importance of this objective in her political strategy.

Conclusions

Recently, climate economics has reconciled welfare maximizing cost-benefit analysis set by the Paris Agreement in 2015 [21, 20, 44]. However, climate adaptation, only implicitly included in those recent assessments [31], together with explicit consideration of uncertainty and of the corresponding interacting and self-adaptive behavior of the decision maker, have been overlooked and require a more thorough examination.

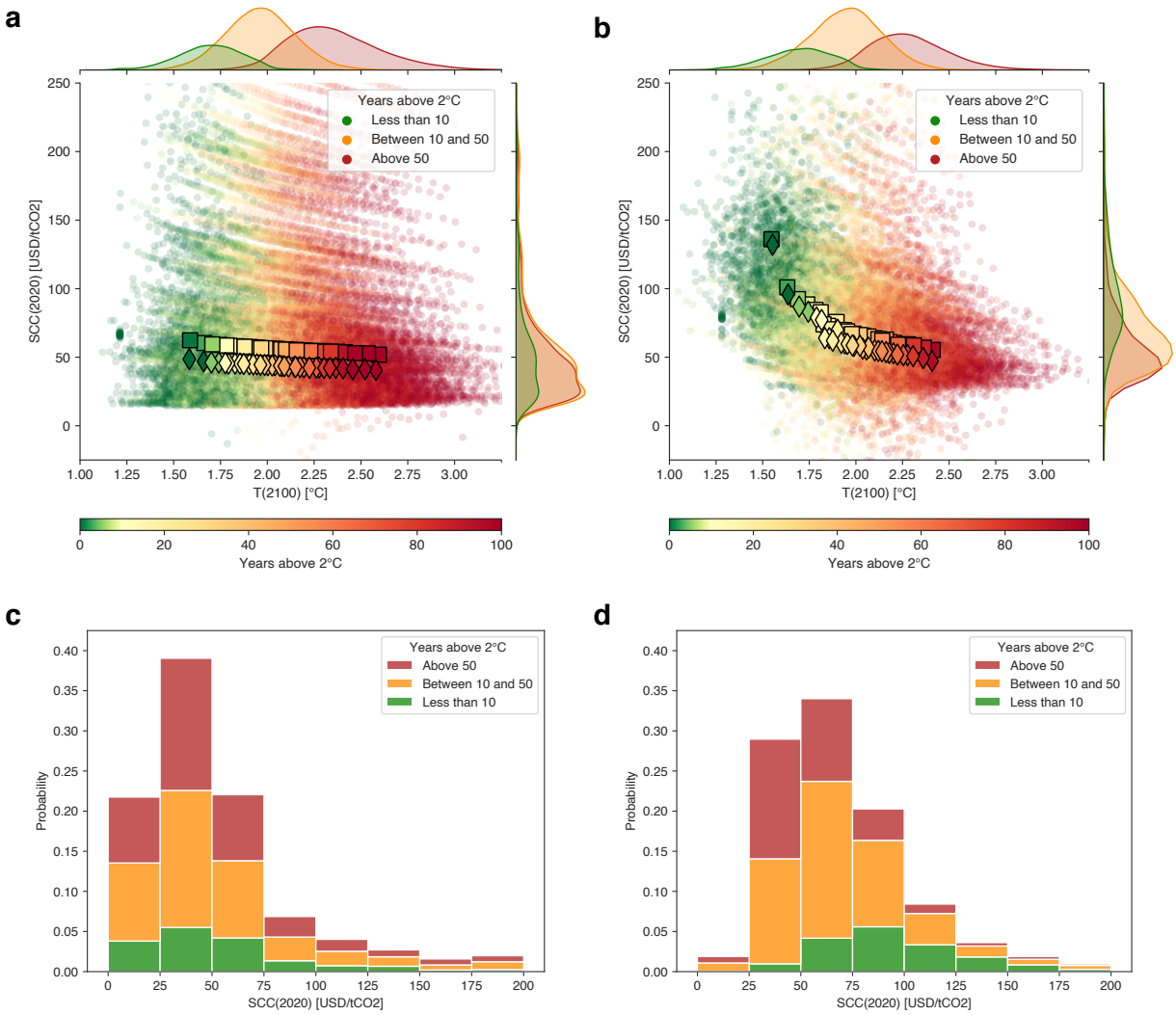

Figure 5: Social cost of carbon estimates across the Pareto optimal set of alternatives using static (a) and self-adaptive (b) climate policies: squares represent mean values while diamonds report the median. The probability of the temperature threshold outcome for a given social cost of carbon estimate is reported for static (c) and self-adaptive climate policy (d).

We confirm previous research results [32, 33, 35] showing that reintroducing adaptation in the cost-benefit IAM DICE produces a climate policy leaning towards adaptation resulting in conflict between the economic and the temperature objective. This is further amplified in presence of uncertainty and in absence of a coherent decision-making model.

By adopting a self-adaptive and multi-objective decision-making model, we show that this conflict can be mitigated, lowering costs of achieving climate targets agreed within the Paris Agreement by 2 trillion USD. The improvement is largely driven by the possibility of adjusting climate policy to the unfolding coupled socio-climatic scenario, especially with respect to adaptation strategies. As adaptation costs in the long term are better managed, more economic resources are made available to increase mitigation effort in the short term and keep temperatures within safer levels. The latter remains the most robust solution to reduce climate risk in the long term.

Finally, we examine the repercussions of the self-adaptive decision making model presented over the social cost of carbon comparing results with the traditional static climate policies. The inherent uncertainty affecting this metric is better characterized across the Pareto optimal trade-off strategies between economic and temperature objective. Furthermore, this results also in a simple instrument to elicit and uncover political preferences between the two objectives based on the adopted social cost of carbon.

In conclusion, cost-benefit IAMs such as DICE need to include explicit adaptation strategies and directly confront the uncertain factors affecting the coupled socio-climatic system considered. The traditional static approach cannot fully represent the capacity to adapt and adjust climate policy as new information emerges and does not reflect the different interests involved in the decision-making process: the economic point of view has to be harmonized with social and political targets. To this aim, we present here an instrument to improve decision-making in DICE overcoming these weaknesses, reducing conflict between economic welfare and temperature increase fostering a clear and open debate over the political nature of possible alternatives to be considered.

Methods

The results reported in this paper are obtained by simulating the different climate policies with 1000 scenarios not used in the climate policy design phase. The simulations are run using the most recently updated DICE model [20], modified to explicitly account for adaptation and uncertainty of the stochastic, parametric and structural nature. The climate policies are designing by optimizing decision variables or control policies, for the static and self-adaptive climate policies respectively, over 400 scenarios.

DICE model

The simulation model used in this work is based on CDICE, a DICE simulation model [50], modified in order to reproduce recent climate economics advances [20] and to explicit consider uncertainty, adaptation and self-adaptive decision making. To align CDICE with most recent results in climate economics, the following components of the CDICE code are updated: i) carbon cycle, which is now based on FAIR [80, 81]; ii) temperature dynamics model, compatible with more recent climate science [82]; iii) climate damages, based on a meta-analysis aimed at removing non-independence bias of the different estimates [19]; iv) forcing of other GHGs, based on the output of REMIND model consistent with SSP 2, the central shared socio-economic pathway; v) rate of decarbonization and the availability of negative emissions techonologies (NETs), following the hypotheses made in [20]. Nonetheless, we don't use the set of pure rate of social time preference and inequality aversion parameters but we rely on default DICE parameters for the purpose of this work.

FAIR climate model simulation

The carbon cycle component of the CDICE code is updated in order to consider more recent advances in the climate science by adopting the carbon cycle of the FAIR (Finite Amplitude Impulse Response) model [80, 81]. This updated component can't be run as a simulation model as it requires solving a nonlinear equation describing the dependence of carbon uptake of the different sinks on the temperature increase and on the total accumulated carbon in the land and ocean sinks. In order to avoid the computational burden of solving a nonlinear equation at each time step and provide a lightweight simulation tool, we calibrate an ANN model solving offline the equation for a plausible range of temperature and carbon concentration in land and ocean sinks values. Adopting this simplification it is possible to compute the state dependent parameter regulating carbon uptake with a 3% error with respect to the true solution for the domain of interest and provide a faster simulation tool.

Adaptation modelling

We model adaptation strategies considering two fundamental mechanisms: flow and stock adaptation, as previously did in the available scientific literature for adaptation in IAMs, and specifically in DICE [33]. Flow (or temporary) adaptation corresponds to actions that reduce climate damages in the short term without affecting longer-term damages such as changes in agricultural practices, energy expenditures for space heating and cooling. On the other hand, stock adaptation describes those actions which allow climate damages reduction in the longer term by building an adaptation capital stock subject to depreciation in time. This second mechanism is supposed to model infrastructural investment such as sea walls, water storage and irrigation facilities, disaster early warning systems. We therefore consider two additional decision variables for each time step: flow (or temporary) adaptation and investment in adaptation stock. Equations and parameters used for this component of the model come from a previous work [33].

Stochastic disturbances

In order to account for natural variability in the climate and shocks in the economy, we consider three stochastic disturbances affecting the dynamics of atmospheric temperature, carbon intensity and total factor productivity. As for the atmospheric temperature, we simulate annual atmospheric temperature from 1860 to 2018 using the dynamic model included in DICE and the radiative forcing from the control period of the RCP database [83]. By comparing simulated temperature and observed data from HadCRUT4 dataset [84], we can estimate the parameters to define an additive disturbance distributed as a normal random variable. A similar approach is adopted to estimate the disturbance in carbon intensity and total factor productivity. In this case, we rely on the World Bank dataset [85] for CO2 emissions and population, on the Investment and Capital Stock Dataset provided by International Monetary Fund [86] for GDP, Capital Stock, Investments and to compute Total Factor Productivity. The years covered by the different datasets range from 1960 to 2014. With regards to the carbon intensity, we estimate a multiplicative disturbance distributed as a Cauchy distribution, truncated in line with maximum and minimum model errors observed in the past. For the total factor productivity, we find that the best fit of past model errors is given by an additive disturbance distributed as a

Cauchy random variable, with a truncation based on the maximum and minimum model errors observed in the past value.

Parametric uncertainty

A complete set of uncertain parameters with their respective range of variation is given in [50]. We rely on those to explore parametric uncertainty for abatement costs, population, total factor productivity and carbon intensity growth. We sample all of these parameters from uniform random variables as the uncertainties are provided as ranges without any probability distribution and we are not able to better characterize the uncertainty of these parameters. Equilibrium climate sensitivity, a key uncertainty of the climate model component, is described using a lognormal distribution fitted on data available in the scientific literature [87]. For what concerns uncertainty on climate adaptation, we add a parameter regulating adaptation efficiency so that for the same expenditure in adaptation the actual reduction in damages is then multiplied by a factor that is sampled from a uniform random variable which ranges from 0 to 2. This allows to explore both scenario where adaptation allows for a great reduction in climate damages and scenarios where adaptation is almost useless as incapable of reducing climate damages.

Model uncertainty

Finally, model uncertainty is represented to describe the uncertainty over climate damages specification as we consider the possibility of incurring in different specification for each simulation by including a surrogate model reproducing econometric results [6, 16]. Therefore, both for the optimization and the validation process, each solution is simulated accounting both for climate damages in line with the recent meta-analysis of expert-elicited estimates [19] or macroeconometric evidence [6, 16]. In the model, we assumed that the two formulations are equiprobable, therefore, both damages specifications are used to simulate an equal number of scenarios to compute average objective values.

Empirical damages surrogate model

To build a surrogate model replicating econometric estimates of climate damages [6], we rely upon the code provided by the authors to simulate different warming scenarios using the same SSP scenario to compute impacts on the economy along the 21st century. Then we aggregate them from country level to global level and study the relationship between the 5-year increase in these damages as percentage of GDP with respect to previous level of damage and temperature level. We find that indeed a second order polynomial function can accurately reproduce the trajectory of damages as percentage of GDP over the next century under different level of warming. This polynomial approximation is included in the model and it is used to describe the evolution in time of damages during the simulation process.

Single objective problem formulations

The objective function to be maximized in the original DICE model is the welfare, which is a function of utility and population:

$$J^{econ} = \sum_{t=0}^{H-1} \frac{U_t}{(1+\rho)^t} \tag{1}$$

where U_t is the utility function depending on consumption per capita, ρ is the discount rate and H is the time horizon. By adopting a notation common in environmental systems and control literature [88, 89, 90] and considering the DICE model as a dynamic system with a state vector $\mathbf{x}_t$, a vector of exogenous states or deterministic disturbances $\mathbf{w}_t$, a vector of stochastic disturbances ε_t, a vector of control (or decision variables) $\mathbf{u}_t$ and a vector of uncertain parameters ξ, we can describe its evolution in time using the set of state transition equations representing model uncertainty indexed by k:

$$\mathbf{x}_{t+1} = \mathbf{f}_k(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t, \boldsymbol{\varepsilon}_{t+1}; \boldsymbol{\xi}) \tag{2a}$$
$$\boldsymbol{\varepsilon}_{t+1} \sim \boldsymbol{\phi}_t^{\boldsymbol{\varepsilon}}(\cdot) \tag{2b}$$
$$\boldsymbol{\xi} \sim \boldsymbol{\phi}^{\boldsymbol{\xi}}(\cdot) \tag{2c}$$
$$k \sim \phi^k(\cdot) \tag{2d}$$
$$\{\boldsymbol{w}_t\}_{t=0,\dots,H-1} \quad given \tag{2e}$$
$$\boldsymbol{x}_0 \quad given \tag{2f}$$
$$t = 0, ..., H-1 \tag{2g}$$

where the state vector $\mathbf{x}_t$ contains the capital stock, the temperature of the atmosphere and of the ocean, the mass of carbon in the atmosphere, the capital adaptation stock available and the current time step. The control vector $\mathbf{u}_t$ contains the decision variables, i.e the emissions control rate, the savings rate and the investments in flow (or temporary) adaptation and in adaptation capital stock. The exogenous trajectories $\mathbf{w}_t$ supplied to the model are the other economic processes whose dynamic is not controllable. The horizon length H is 100, consisting of 5-years time step, covering from 2015 to 2515. These general system dynamics equation are used to examine different modelling assumptions: first we use them to study the introduction of uncertainty and adaptation. To this aim, only static optimization problems are formulated. In particular, we first reproduce the recent climate economics results [20] by solving a deterministic problem where adaptation is not explicitly modelled as follows:

$$\max_{\{\mu_t, s_t\}_{t=0,\dots,H-1}} J^{econ} \tag{3a}$$
$$\mathbf{x}_{t+1} = \mathbf{f}_{\sim adapt}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \tag{3b}$$
$$\{\boldsymbol{w}_t\}_{t=0,\dots,H-1} \quad given \tag{3c}$$
$$\boldsymbol{x}_0 \quad given \tag{3d}$$
$$t = 0, ..., H-1 \tag{3e}$$

where $\{\mu_t, s_t\}_{t=0,\dots,H-1}$ represent the decision variables over the time horizon (emission control rate and savings rate). After that we solve a model considering uncertainty explicitly but no adaptation yet:

$$\max_{\{\mu_t, s_t\}_{t=0,\dots,H-1}} \quad \underset{\{\boldsymbol{\varepsilon}_t\}_{t=0,\dots,H-1}, \boldsymbol{\xi}, k}{E} J^{econ} \tag{4a}$$
$$\mathbf{x}_{t+1} = \mathbf{f}_{k, \sim adapt}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t, \boldsymbol{\varepsilon}_{t+1}; \boldsymbol{\xi}) \tag{4b}$$
$$\boldsymbol{\varepsilon}_{t+1} \sim \boldsymbol{\phi}_t^{\boldsymbol{\varepsilon}}(\cdot) \tag{4c}$$
$$\boldsymbol{\xi} \sim \boldsymbol{\phi}^{\boldsymbol{\xi}}(\cdot) \tag{4d}$$
$$k \sim \phi^k(\cdot) \tag{4e}$$
$$\{\boldsymbol{w}_t\}_{t=0,\dots,H-1} \quad given \tag{4f}$$
$$\boldsymbol{x}_0 \quad given \tag{4g}$$
$$t = 0, ..., H-1 \tag{4h}$$

Then, we introduce explicit adaptation modelling - i.e. we add the decision variables ia_t and fad_t representing investment in adaptation stock and temporary adaptation expenditures respectively - by first solving a deterministic problem:

$$\max_{\{\mu_t, s_t, ia_t, fad_t\}_{t=0,\dots,H-1}} J^{econ} \tag{5a}$$
$$\mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \tag{5b}$$
$$\{\boldsymbol{w}_t\}_{t=0,\dots,H-1} \quad given \tag{5c}$$
$$\boldsymbol{x}_0 \quad given \tag{5d}$$
$$t = 0, ..., H-1 \tag{5e}$$

and the corresponding fully uncertain problem, also used to validate all the found climate policies, simulate their dynamics and prepare the figures reported:

$$\max_{\{\mu_t, s_t, ia_t, fad_t\}_{t=0,\dots,H-1}} \quad \underset{\{\boldsymbol{\varepsilon}_t\}_{t=0,\dots,H-1}, \boldsymbol{\xi}, k}{E} J^{econ} \tag{6a}$$
$$s.t. \quad Eq.2 \tag{6b}$$

The solution to this last problem is also the one representing a single objective when compared against two-objective solutions.

Multi-objective problem formulations

For the multi-objective solutions we add a second objective which counts the number of time steps of model simulations where the atmospheric temperature is above 2°C (to be minimized):

$$J^{clim} = \frac{1}{H} \sum_{t=0}^{H-1} \begin{cases} 1 & T \geq 2 \\ 0 & T \leq 2 \end{cases} \tag{7}$$

The solutions in this case are derived from two different problem formulations: in the first, we maintain the static optimization procedure, i.e. we fix the decision variables but optimizing with respect to two objectives:

$$\min_{\{\mu_t, s_t, ia_t, fad_t\}_{t=0,\dots,H-1}} \quad \underset{\{\boldsymbol{\varepsilon}_t\}_{t=0,\dots,H-1},\boldsymbol{\xi},k}{E} [-J^{econ} \quad J^{clim}] \tag{8a}$$

$$s.t. \quad Eq.2 \tag{8b}$$

To implement self-adaptive decision making, we then formulate a multi-objective optimal control problem as follows:

$$\min_{p} \quad \underset{\{\boldsymbol{\varepsilon}_t\}_{t=0,\dots,H-1},\boldsymbol{\xi},k}{E} [-J^{econ} \quad J^{clim}] \tag{9a}$$

$$s.t. \quad Eq.2 \tag{9b}$$

$$\mathbf{u}_t = [\mu_t, s_t, ia_t, fad_t] \tag{9c}$$

$$\mathbf{u}_t = p(\mathbf{x}_{t+1}, t) \tag{9d}$$

where a control policy p is a policy taking as input the state of the system and returning as output the decision variables.

Optimization algorithms

To solve the optimization problems formulated above we use a simulation based optimization methodology relying on the Borg multi-objective evolutionary algorithm [91] that has been demonstrated to produce a similar or better performance with respect to other state of the art evolutionary algorithms [92]. Borg relies on adaptive genetic operators to iteratively generate new solutions and converge to the Pareto-optimal ones. It is also able to detect stagnation in the search process as well as to randomize restarts in order to avoid local optima. Borg is used directly to fix the decision variables when solving a static intertemporal optimization problem. On the other hand, to solve the optimal control problem we adopt the EMODPS algorithm [93, 70], which is an approximation of stochastic dynamic programming [94, 95]. First, we assume that the shape of the policy is described by an artificial neural network - with radial basis activation functions - for their universal approximating capabilities [96, 97, 98]. Second, we search for the Pareto-optimal parametrizations of the assumed policy using Borg. The EMODPS algorithm has been already applied successfully in different environmental systems case studies where multi-objective self-adaptive decision making helps in exploring trade-offs and be reactive with respect to uncertainty [99, 70, 100, 101, 102]. In our specific case the policy takes in input a reduced state composed of the following six variables: the total carbon concentration in the atmosphere, the temperature in the atmosphere, the temperature in the ocean, the current time step, the adaptation stock capital and the capital stock divided by total factor productivity and population, i.e. the capital stock in effective labor units [56, 103]. This last reformulation of the capital stock is fundamental in order to have a more meaningful indicator of the state of the system: as the capital stock is increasing over all the simulation time, its value by itself it is not very meaningful for the control policy. By condensing in this variable information about the general evolution of economy and by including the effect induced by variability in population and total factor productivity, the policy can take advantage of a more representative indicator of the economy.

Data and Code Availability

The simulation model, the characterization of uncertainties, the calibration of surrogate econometric damages model and FAIR climate model simulation model are available at the following GitHub repository (`https://github.com/EILab-Polimi/ADDICE`). Also the scripts for replicating the figures reported in the paper are available at the same repository.

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Figures

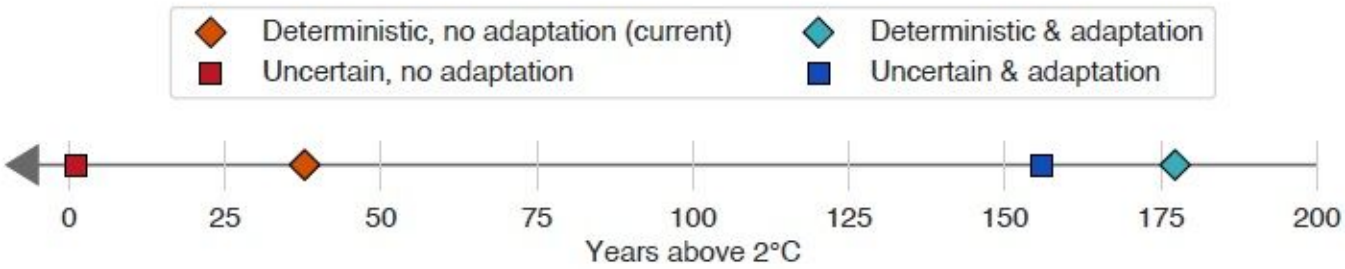

Figure 1

Implications for Paris Agreement compliance using the traditional static welfare maximization decisionmaking model. Uncertainty makes lower temperature economically favorable but including adaptation leads to a resurgence of the conflict between economic optimality and climate stabilization.

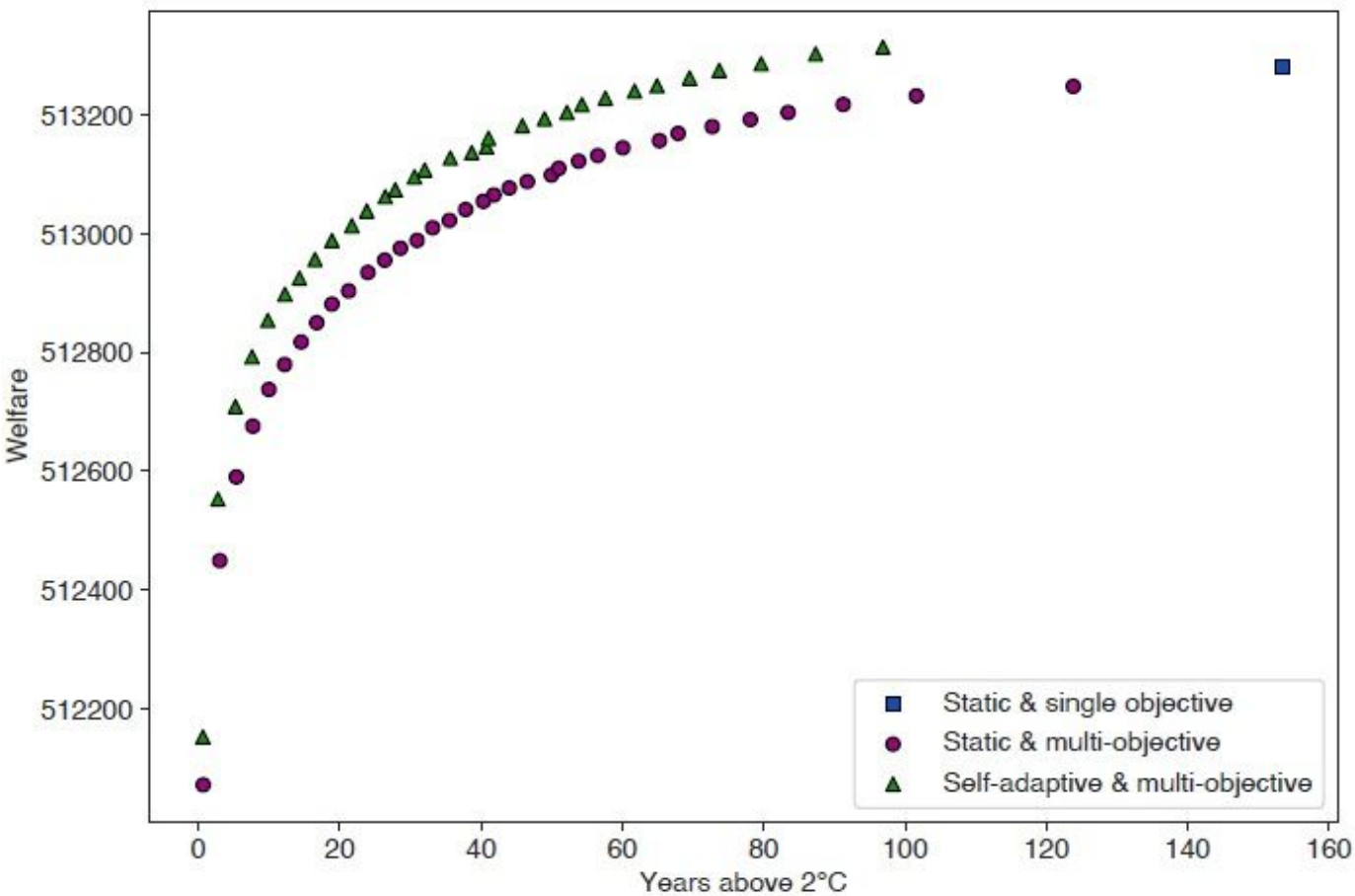

Figure 2

SACPs can largely reduce the conflict between economic and institutional perspective as the Pareto front moves in the direction of preference for both temperature and economic objectives with respect to multi-objective static climate policies. The static single objective climate policy presents a stark contrast between the two objectives and reports the worst outcome in terms of 2°C overshoot.

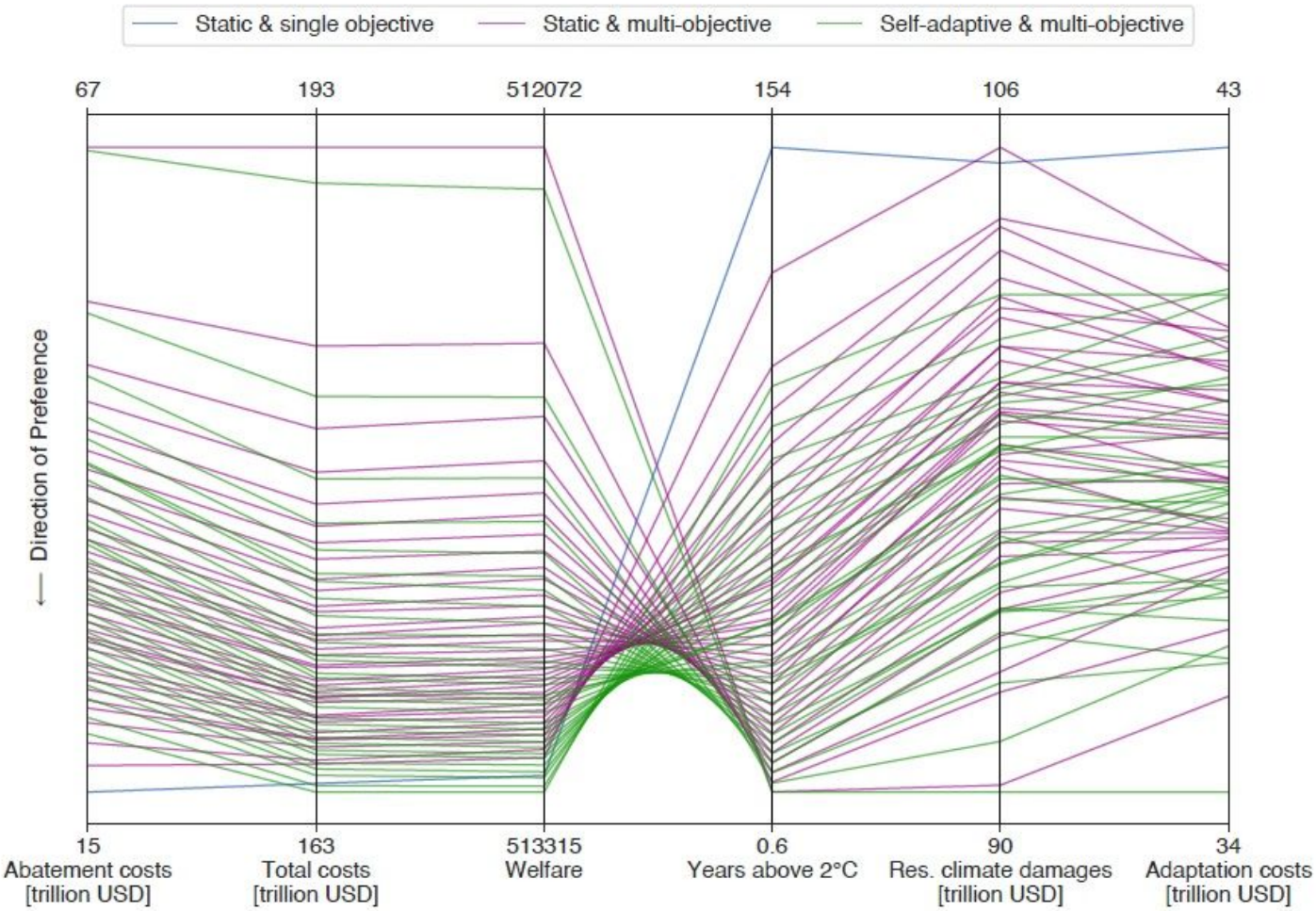

Figure 3

Models' performance with respect to different cost metrics and the two objectives considered, namely, welfare and years above 2°C. For each metric and objective considered, the preferred value lies at the bottom end of each axis. Cost metrics are reported as net present value trillion USD and are computed using Ramsey discounting.

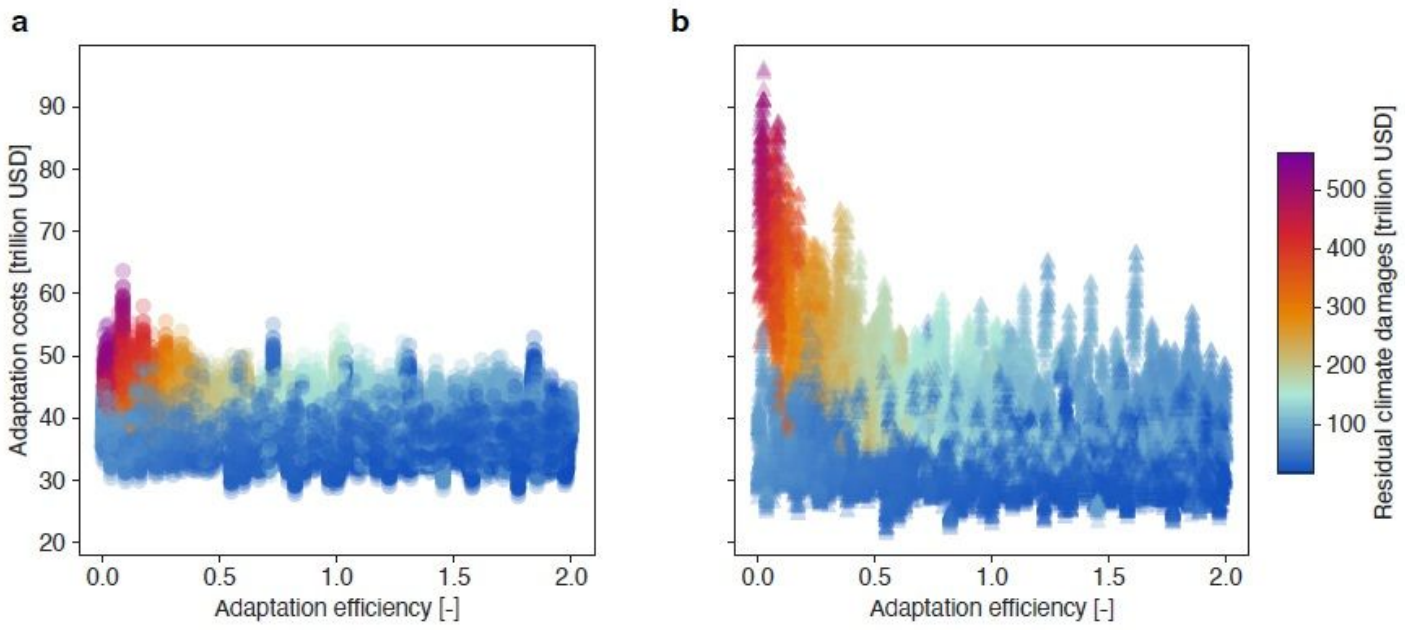

Figure 4

Adaptation costs for static (a) and self-adaptive (b) climate policies are reported against the adaptation efficiency and residual climate damages. Self-adaptive climate policies modulate the adaptation effort proportionally to residual climate damages and inversely proportional to adaptation efficiency.

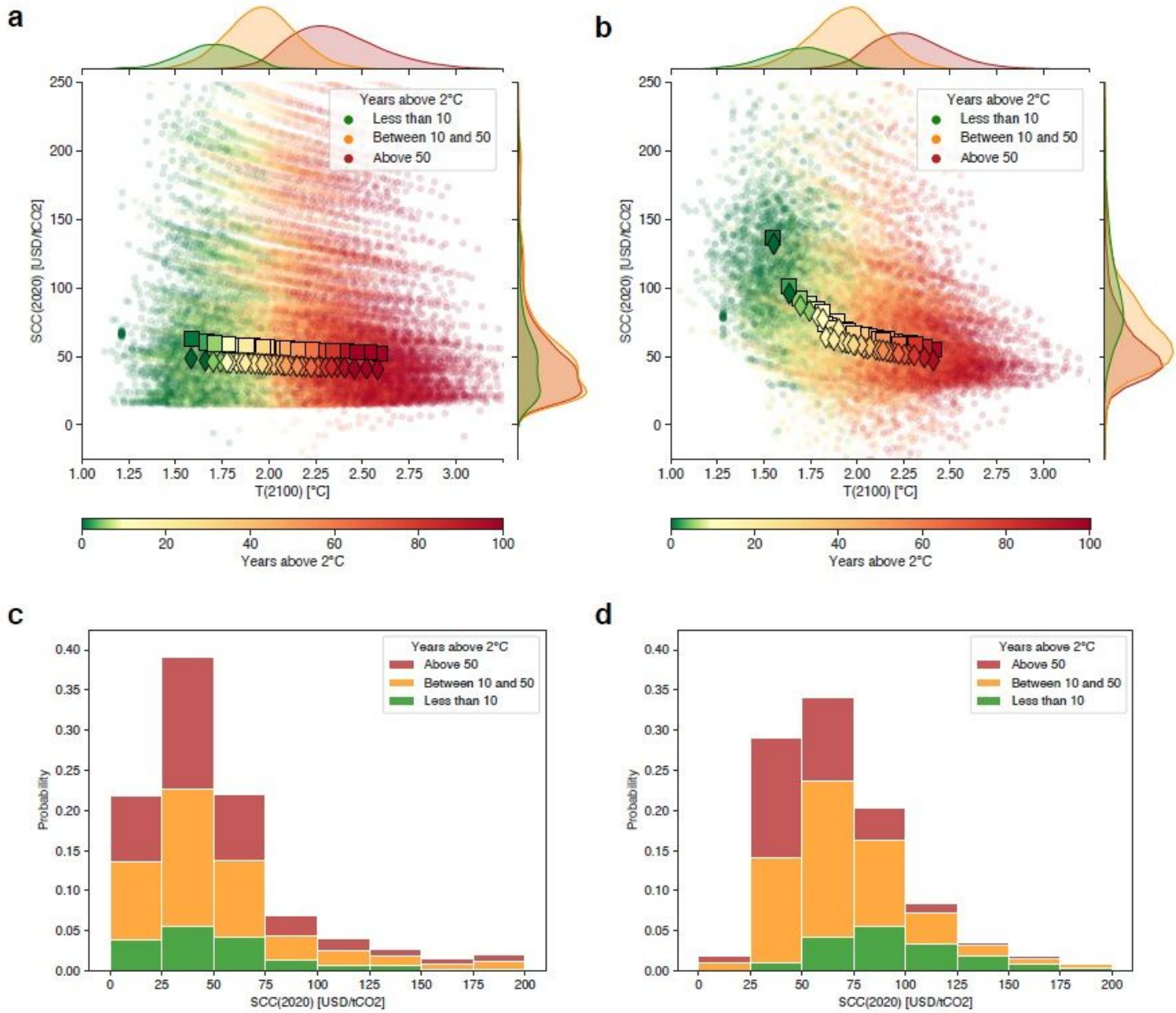

Figure 5

Social cost of carbon estimates across the Pareto optimal set of alternatives using static (a) and self-adaptive (b) climate policies: squares represent mean values while diamonds report the median. The probability of the temperature threshold outcome for a given social cost of carbon estimate is reported for static (c) and self-adaptive climate policy (d).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.pdf