

# Earth's Future

## RESEARCH ARTICLE

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### Key Points:

- Dealing explicitly with conflicting objectives, multi-objective climate policies align mitigation, and adaptation strategies
- Self-adaptive multi-objective policies provide the best objectives' trade-offs by flexibly balancing mitigation and adaptation strategies
- Any climate action delay sharpens the conflicts between the objectives and reduces the benefits associated with self-adaptive policies

### Supporting Information:

Supporting Information may be found in the online version of this article.

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## Self-Adaptive Multi-Objective Climate Policies Align Mitigation and Adaptation Strategies

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**Abstract** Intensifying climate change impacts can divert the economic resources away from emission reduction toward adaptation to reduce rising damages, jeopardizing temperature stabilization within safe levels. Indeed, the traditional static welfare-maximizing climate policy design leads to a conflict between mitigation and adaptation, invalidating the recently established consistency of cost-benefit analysis with the Paris Agreement's targets. Here, we show that this tension can be resolved by integrating multi-objective optimization and feedback control in the Dynamic Integrated Climate Economy model to design self-adaptive climate policies trading off welfare maximization with the Paris Agreement compliance. These policies allow adjusting against uncertainty as information on the socio-climatic system accumulates, thus representing the policy-making process more realistically. We show that, the costs being the same as in traditional methods, warming above 2°C and the probability of overshooting can be drastically reduced, emphasizing the need for integrating adaptation and mitigation strategies and the value of embracing a self-adaptive, multi-objective perspective.

**Plain Language Summary** Traditionally, computer models are used to study the timing and magnitude of greenhouse gases emissions reduction, adopting an economic perspective. Yet, some well-known major issues affect such analyses. First, the decisions need to be taken in an uncertain context, that is, without exact knowledge about the future evolution of climate and economy. Second, these decisions should be contemplating multiple climate policy targets and objectives simultaneously. Third, decisions can be refined and adjusted as we gain more information about the economy, the climate, and their interactions. Finally, climate adaptation strategies, that is, actions and policies that can reduce a part of future climate impacts, are often overlooked as they are treated implicitly. While the models have been improved over time, these problems have never been examined all at once. In this work, we explicitly consider climate adaptation and jointly solve the above issues to show that mitigation and adaptation strategies can be adjusted flexibly to reduce conflicts between different climate policy objectives. Yet, to achieve good performance across the indicators examined, fast climate action is required.

## 1. Introduction

Social and economic impacts of climate change have become increasingly studied and quantified over the last years (Auffhammer, 2018; Carleton & Hsiang, 2016) and are on the rise (Coronese et al., 2019; Field et al., 2012). Econometric assessments rely on panel data and regression models to explain observed relationships between socio-economic and climatic variables over time and across different geographical regions (Burke et al., 2015; Dell et al., 2012). This methodology reveals the strong interconnections between climate trends or shocks and socio-economic indicators at the sector and aggregated level (Differbaugh & Burke, 2019; Hsiang et al., 2011, 2013, 2017; Kotz et al., 2021; Lobell & Field, 2007; Lobell et al., 2011; Schlenker & Roberts, 2009).

Substantial losses result from projecting the estimated economic response to climatic variables into the future for the global economy (Burke et al., 2018; Kahn et al., 2019; Moore & Diaz, 2015), with estimates of average global reduction of gross domestic product (GDP) per capita in 2,100 in the order of 30% with respect to a baseline high emissions scenario (Burke et al., 2015), one order of magnitude larger than with expert-elicited damage functions used in the Dynamic Integrated Climate Economy (DICE) model and other cost-benefit integrated assessment models (IAMs) (Howard & Sterner, 2017; Nordhaus, 2017). Even though the debate over the 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 (Glanemann et al., 2020; Hänsel et al., 2020), in line with the Paris Agreement (UNFCCC, 2015). Yet, as climate impacts intensify, economic resources shift from mitigation to adaptation is a severe risk (Adger, 2006; Field et al., 2014; Smit & Wandel, 2006).

Given the potential societal and economic benefits of the effective implementation of adaptation strategies and the inevitable need to cope with future climatic conditions (Hoegh-Guldberg et al., 2019; Parry et al., 1998; Sherwood, 2020), the quest for the optimal mix of mitigation and adaptation has been a long-standing issue in climate policy design (Klein et al., 2005; Moser, 2012). To explore synergies and conflicts between mitigation and adaptation, cost-benefit IAMs, which initially describe adaptation implicitly (Füßel, 2010), have introduced various compact form representations of its fundamental working principles (Agrawala, Bosello, Carraro, De Bruin et al., 2011; Agrawala, Bosello, Carraro, De Cian, & Lanzi, 2011; Bahn et al., 2019; De Bruin et al., 2009). When a climate policy is designed contemplating this additional lever, the transition to carbon neutrality is delayed, confirming results obtained for the energy and power sector (Handayani et al., 2020; Kopytko & Perkins, 2011). Even though IAMs including adaptation modeling have been criticized for their simplicity (Patt et al., 2010), they remain a valuable tool to explore the interplay between mitigation and adaptation in climate policy, analyze key relationships and identify critical areas requiring further research (Bretschger & Pittel, 2020; Fankhauser, 2017; Weyant, 2017). For this reason, IAMs should improve their representation of adaptation rather than treating it implicitly to avoid the burden associated with it.

Here, we show that the introduction of adaptation in DICE delays mitigation and jeopardizes the chance of meeting the Paris Agreement invalidating recent results on its economic optimality (Glanemann et al., 2020; Hänsel et al., 2020). Yet, three fundamental assumptions on which DICE is based dispute the above point and motivate a modeling shift to address them quantitatively. These are the deterministic nature of DICE (Cai et al., 2016; Felgenhauer & De Bruin, 2009), the corresponding static (once for all) design of climate policies (Ekholm, 2018; Felgenhauer & De Bruin, 2009; Garner & Keller, 2018; Marangoni et al., 2021; Mathias et al., 2017), and its single-objective characterization (Garner et al., 2016; Marangoni et al., 2021). Indeed, the traditional static intertemporal optimization adopted to design emissions reduction and adaptation investments decisions once and for all fails in realistically reproducing the evolution of climate policy in response to changes in the socio-economic and climatic system. Moreover, its application over many uncertain future scenarios can result in contradictory policy recommendations (Crost & Traeger, 2013). We introduce the concept of self-adaptive climate policies (SACPs) to describe how climate policy decisions can change depending on the evolving socio-climatic state of the system. Specifically, SACPs close the loop between the information available to a decision-maker in a given time (e.g., temperature, carbon dioxide concentration, global economy, and adaptation capital stock) and his/her subsequent action (e.g., annual emissions and investment in adaptation measures) in response to this new system state. Adaptation also seems to be the climate policy constituent that might benefit the most from the improved decision-making realism that this technique yields (Herman et al., 2020). Formally, an SACP is an optimal feedback control policy. While previous applications of optimal control theory in climate policy range from stochastic and approximate dynamic programming (Cai et al., 2015, 2016; Jensen & Traeger, 2014; Lemoine & Rudik, 2017; Lontzek et al., 2015; Webster et al., 2012) to model predictive control (Kellett et al., 2019; Weller et al., 2015), the methodology adopted here is designed to reduce the computational burden associated with the curse of dimensionality, modeling, and multiple objectives (Giuliani et al., 2018).

The single-objective welfare-maximizing problem formulation is another major limitation of DICE. Indeed, it does not allow to explain the complex and multi-faceted nature of climate policy and recent carbon neutrality plan declarations. Not trespassing the 2°C warming threshold must be acknowledged as a critical objective since the occurrence of that event would significantly increase the risk of catastrophic climate damages (Lenton et al., 2008; Steffen et al., 2018), an undesirable outcome from a socio-political perspective (Okereke & Coventry, 2016; Schleussner, Lissner, et al., 2016; Schleussner, Rogelj, et al., 2016). 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 (Stern et al., 2019). While multi-objective optimization has been adopted to reveal the conflicts between many objectives in climate policy (i.e., welfare, temperature, and the different costs components) (Garner et al., 2016),

it has not been coupled yet with self-adaptive decision-making to evaluate the consequential reduction in conflicts between the alignment of mitigation and adaptation strategies.

In this paper, we update a simulation version of DICE (Garner et al., 2016; Lamontagne et al., 2019) with the most recent improvements to the model (Hänsel et al., 2020). We re-introduce explicit adaptation choices as short-term actions and long-term investments in adaptation stock (Agrawala, Bosello, Carraro, De Bruin et al., 2011) to assess the importance of the abovementioned points. First, we directly include uncertainty—stochastic, parametric, and structural—over both the physical and the socio-economic model components, also covering key uncertain factors such as adaptation efficiency and climate damages specification. Second, as deep uncertainty in the modeled evolution of the coupled socio-economic and climatic systems (Ackerman & Stanton, 2012; Ackerman et al., 2010; Anthoff & Tol, 2014; Butler et al., 2014; Gillingham et al., 2018; Lamontagne et al., 2019; Nordhaus, 2018; Pindyck, 2013, 2017) calls for an adaptive decision-making approach in climate policy and integrated assessment modeling (Allen & Frame, 2007; Haasnoot et al., 2013; Pizer, 1999), 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 (Giuliani et al., 2018) to transparently reveal the conflicts between welfare maximization and compliance with the Paris Agreement, exploring the set of Pareto-optimal alternatives.

Here, we analyze the integration of these previously individually analyzed different components into a single unified and coherent modeling framework, including the effect of adaptation investment as an explicit decision variable. We demonstrate that self-adaptive multi-objective climate policies reduce the conflict between the objectives and balance mitigation and adaptation strategies flexibly based on the realization of uncertainties and the socio-climatic system's evolution.

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 due to the ability to flexibly manage mitigation and adaptation options depending on the current realization of each scenario to reduce total climate policy costs, that is, mitigation and adaptation costs and climate damages. As both net damage and adaptation costs are decreased significantly via SACPs, more economic resources are available in the short term to increase abatement efforts and keep warming within safe limits without compromising the level of welfare. As a consequence, the probability of overshooting 2°C and warming above this threshold is reduced, especially for less favorable scenarios. As many targets are discussed in climate policy design, we show that approaches explicitly considering the inherent uncertainty and the potential to adjust decisions and balance the different objectives dynamically can reduce conflicts between these and motivate increased ambition in decarbonization efforts.

## 2. Methods

We base our analysis on a simulation version of DICE rewritten to accommodate the purpose of the study. Indeed, we expand the model to account for recent climate-economics advancements such as alternative climate damages (Burke et al., 2015) and abatement costs (Grubb et al., 2021) specifications, explicit adaptation modeling (Agrawala, Bosello, Carraro, De Bruin et al., 2011), stochastic, parametric, and structural uncertainty. Moreover, we substitute the climate component of DICE with the Finite Amplitude Impulse Response (FAIR) climate emulator (Millar et al., 2017; Smith et al., 2018). We use this extended model to test and compare two decision-making models: the traditional static intertemporal optimization method and a dynamic self-adaptive approach (Giuliani et al., 2018). We calibrate the climate policies over 100 scenarios (or only a reference scenario if a deterministic approach is adopted). After calibration, multi-objective solutions that result in a very poor performance in the welfare metric have been discarded from the analysis. We do so by adopting the Certainty Balanced Growth Equivalent (CBGE) (Anthoff & Tol, 2009) metric to better interpret welfare. If the CBGE loss is above 5%—with respect to the single-objective welfare-maximizing static climate policy considering uncertainty and explicit adaptation—solutions are removed. The remaining solutions are validated over 1,000 scenarios which are used to broaden the sampled set of future states of the world and to ensure that there is no over-fitting to the calibration scenarios. These scenarios are obtained by sampling the full set of socio-economic and physical uncertainties discussed in detail in Supporting Information S1.

## 2.1. The DICE Model

The DICE model (Nordhaus, 2017) is a cost-benefit IAM used to study the economically optimal control of greenhouse gases (GHGs) emission over time, that is, to find the balance of costs and benefits of reducing emissions and maximizing social welfare, computed as the sum of discounted utility per time period. It comprises two modules describing the evolution of the global aggregated economy and the climate system. The model has a time step of 5 years and is simulated for 500 years starting from 2015. We consider recent updates to the model (Glanemann et al., 2020; Hänsel et al., 2020) as climate damages specifications, climate module update, forcing of other GHGs. We expand the model introducing explicit adaptation modeling (Agrawala, Bosello, Carraro, De Bruin et al., 2011), speeding up the computational time of the climate emulator, and simulating stochastic, parametric, and structural uncertainty in both the climate and socio-economic components. In particular, we use the FAIR climate emulator in the CO<sub>2</sub>-only mode with other GHGs forcings obtained from the Representative Concentration Pathways (RCPs) scenarios (Van Vuuren et al., 2011). We reduce computational time for its simulation by using a nonlinear model to estimate the absorption efficiency of land and ocean carbon sinks as a function of temperature and carbon accumulated in these. With respect to climate damages, we consider both level-type (Howard & Sterner, 2017) and growth-type (Burke et al., 2015) formulations, building a surrogate model reproducing more detailed regional models. Regarding adaptation, we rely on the mechanism first described in (De Bruin et al., 2009) and improved in (Agrawala, Bosello, Carraro, De Bruin et al., 2011). In this, adaptation is an additional lever capable of temporarily reducing climate damages in the very short term (flow adaptation) and more in the long-term through investment (stock adaptation). A summary reporting the details on adaptation modeling as well as the uncertainties considered and their derivation is reported in Supporting Information S1.

## 2.2. Traditional Welfare-Maximizing Problem Formulations

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

$$J^{econ} = U \quad (1)$$

where  $U$  is the economic utility as described in Supporting Information S1. Adopting a notation common in the environmental systems planning and control literature (Loucks et al., 1981; Maass et al., 1962; Soncini-Sessa et al., 2007) 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  $\boldsymbol{\varepsilon}_t$ , a vector of control (or decision variables)  $\mathbf{u}_t$ , and a vector of uncertain parameters  $\boldsymbol{\xi}$ , we can describe its evolution in time using the set of state transition equations representing model uncertainty indexed by  $k$

$$\mathbf{x}_{t+1} = \mathbf{f}_k(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t, \boldsymbol{\varepsilon}_{t+1}; \boldsymbol{\xi}) \quad (2a)$$

$$\boldsymbol{\varepsilon}_{t+1} \sim \boldsymbol{\phi}_t^{\boldsymbol{\varepsilon}}(\cdot) \quad (2b)$$

$$\boldsymbol{\xi} \sim \boldsymbol{\phi}^{\boldsymbol{\xi}}(\cdot) \quad (2c)$$

$$k \sim \phi^k(\cdot) \quad (2d)$$

$$\{\mathbf{w}_t\}_{t=0, \dots, H-1} \text{ given} \quad (2e)$$

$$\mathbf{x}_0 \text{ given} \quad (2f)$$

$$t = 0, \dots, H - 1 \quad (2g)$$

where the state vector  $\mathbf{x}_t$  contains the capital stock, the atmosphere's temperature, the concentration 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, that is, the emissions control rate, the savings rate, and the investments in flow (or temporary) adaptation and 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 a 5-year time

step, covering from 2015 to 2515. These general system dynamics equations are used to examine different modeling assumptions: first, we use them to study the introduction of uncertainty and adaptation. To this specific aim, we formulate only static optimization problems. In particular, we first reproduce the recent climate economics results (Hänsel et al., 2020) by solving a deterministic problem where adaptation is not explicitly modeled as follows:

$$\max_{\{\mu_t, s_t\}_{t=0, \dots, H-1}} J^{econ} \quad (3a)$$

$$\mathbf{x}_{t+1} = \mathbf{f}_{adapt}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \quad (3b)$$

$$\{\mathbf{w}_t\}_{t=0, \dots, H-1} \text{ given} \quad (3c)$$

$$\mathbf{x}_0 \text{ given} \quad (3d)$$

$$t = 0, \dots, H - 1 \quad (3e)$$

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 problem considering uncertainty explicitly but no adaptation yet

$$\max_{\{\mu_t, s_t\}_{t=0, \dots, H-1}} E_{\{\epsilon_t\}_{t=0, \dots, H-1}, \xi, k} J^{econ} \quad (4a)$$

$$\mathbf{x}_{t+1} = \mathbf{f}_{k, adapt}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t, \epsilon_{t+1}; \xi) \quad (4b)$$

$$\epsilon_{t+1} \sim \phi_t^\epsilon(\cdot) \quad (4c)$$

$$\xi \sim \phi^\xi(\cdot) \quad (4d)$$

$$k \sim \phi^k(\cdot) \quad (4e)$$

$$\{\mathbf{w}_t\}_{t=0, \dots, H-1} \text{ given} \quad (4f)$$

$$\mathbf{x}_0 \text{ given} \quad (4g)$$

$$t = 0, \dots, H - 1 \quad (4h)$$

Then, we introduce explicit adaptation modeling—that is, we add the decision variables  $IA_t$  and  $FAD_t$  representing investment in adaptation stock and temporary adaptation expenditures, respectively, as explained in Supporting Information S1—by first solving a deterministic problem

$$\max_{\{\mu_t, s_t, IA_t, FAD_t\}_{t=0, \dots, H-1}} J^{econ} \quad (5a)$$

$$\mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \quad (5b)$$

$$\{\mathbf{w}_t\}_{t=0, \dots, H-1} \text{ given} \quad (5c)$$

$$\mathbf{x}_0 \text{ given} \quad (5d)$$

$$t = 0, \dots, H - 1 \quad (5e)$$

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

$$\max_{\{\mu_t, s_t, IA_t, FAD_t\}_{t=0, \dots, H-1}} E_{\{\epsilon_t\}_{t=0, \dots, H-1}, \xi, k} J^{econ} \quad (6a)$$

$$s.t. \quad Eq.2 \quad (6b)$$

The solution to this last problem is also the one representing a single-objective climate policy when compared to many-objective alternatives.

### 2.3. Multi-Objective Problem Formulations

For the multi-objective problem formulation, we have five additional objectives characterizing performance over temperature and economic indicators. In particular, we add a second objective as follows:

$$J^{2C} = \begin{cases} 1 & \exists TATM_t > 2, t = 0, \dots, H \\ 0 & else \end{cases} \quad (7)$$

which averaged over a number  $N$  of simulations gives the probability that a specific climate policy will overshoot the Paris Agreement's threshold. We add a third objective to account for the magnitude of the overshoot above 2°C:

$$J^{2CY} = \sum_{t=0}^{H-1} \begin{cases} TATM_t - 2 & \exists TATM_t > 2 \\ 0 & else \end{cases} \quad (8)$$

which represents the integral of warming above 2°C over the simulation horizon, as in Marangoni et al. (2021).

With respect to economic sector, we include three cost objectives computed at their net present value (NPV) using the real interest rate. These three objectives separate implicit trade-offs hidden behind the welfare definition, as in Garner et al. (2016). Therefore, we aim to minimize NPV abatement costs:

$$J^{ABATE} = \sum_{t=0}^{H-1} \frac{abatecost_t}{(1 + ri_t)} \quad (9)$$

NPV climate impacts:

$$J^{DAMAGES} = \sum_{t=0}^{H-1} \frac{damages_t}{(1 + ri_t)} \quad (10)$$

and NPV adaptation costs:

$$J^{ADAPT} = \sum_{t=0}^{H-1} \frac{adaptcost_t}{(1 + ri_t)} \quad (11)$$

where *abatecost*, *damages*, *adaptcost*, and *ri* represent the abatement costs, the residual climate damages, the adaptation costs, and the real interest rate as discussed in Supporting Information S1. We collect the six objectives we optimize in the following vector:

$$\mathbf{J}^{6OBS} = \begin{bmatrix} J^{ECON} & J^{2C} & J^{2CY} & J^{ABATE} & J^{DAMAGES} & J^{ADAPT} \end{bmatrix} \quad (12)$$

The climate policies that are the solution of this multi-objective problem are derived from two different formulations: in the first, we maintain the static optimization procedure, that is we fix the decision variables but optimizing with respect to two objectives:

$$\min_{\{\mu_t, s_t, I, A_t, FAD_t\}_{t=0, \dots, H-1}} E_{\{\epsilon_t\}_{t=0, \dots, H-1}, \xi, k} [\mathbf{J}^{6OBS}] \quad (13a)$$

$$s.t. \quad Eq.2 \quad (13b)$$

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

$$\min_p E_{\{\epsilon_t\}_{t=0, \dots, H-1}, \xi, k} [\mathbf{J}^{6OBS}] \quad (14a)$$

$$s.t. \quad Eq.2 \quad (14b)$$



$$\mathbf{u}_t = [\mu_t, s_t, I A_t, F A D_t] \quad (14c)$$

$$\mathbf{u}_t = p(\mathbf{x}_t, t) \quad (14d)$$

where a control policy  $p$  is a policy taking as input the state of the system and returning as output the decision variables. For the sake of compactness, we use a reduced state vector as input to the control policy. This considers the atmospheric temperature, the CO<sub>2</sub> concentration in the atmosphere, the capital stock, the adaptation stock, and the time step. Furthermore, as we employ a direct policy search approach, we also embed exogenous relevant information, that is, the observed economic damages of climate change, as an input to the policy. This additional variable, together with the state of the system, provides valuable information on how effective adaptation is and how the spending on adaptation and mitigation should be updated in response to the observed evolution of the socio-climatic system. The approach used here extends the one adopted in Marangoni et al. (2021) as it adopts a full state feedback control scheme.

## 2.4. Optimization Algorithms

To solve the optimization problems formulated above, we use a simulation-based optimization methodology relying on the Borg multi-objective evolutionary algorithm (Hadka & Reed, 2013) that has been demonstrated to produce a similar or better performance with respect to other state-of-the-art evolutionary algorithms (Hadka & Reed, 2012). 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 to avoid local optima. Borg is used directly to optimize the decision variables when solving a static intertemporal optimization problem. On the other hand, to solve the optimal control problem, we adopt the Evolutionary Multi-Objective Direct Policy Search (EMODPS) algorithm (Giuliani, Castelletti, et al., 2016; Giuliani et al., 2018), which approximates stochastic dynamic programming (Bellman, 1958; Bertsekas et al., 1995). 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 (Cybenko, 1989; Funahashi, 1989; Hornik et al., 1989). Second, we search for the Pareto-optimal parametrizations of the assumed policy using Borg. The EMODPS algorithm has already been applied successfully in different environmental systems case studies where multi-objective self-adaptive decision-making helps explore trade-offs and being reactive regarding uncertainty (Bertoni et al., 2019; Garner & Keller, 2018; Giuliani, Anghileri, et al., 2016; Giudici et al., 2019; Giuliani et al., 2018; Quinn et al., 2017). In our specific case, the policy takes into input a reduced state composed of the following six variables: the climate damages observed in the previous time step as a percentage of the global GDP, the total carbon concentration in the atmosphere, the atmospheric temperature, the current time step, the adaptation stock capital, and the capital stock divided by total factor productivity and population, that is, the capital stock in effective labor units (Jensen & Traeger, 2014; Traeger, 2014). This last reformulation of the capital stock is fundamental to having a more meaningful indicator of the system's state. Indeed, as the capital stock increases over all the simulation time, its value would not carry meaningful information for the control policy. By condensing in this variable information about the general evolution of the 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. Furthermore, a piece of exogenous information, the fraction of climate damages after adaptation, is used as additional input to the control policy.

## 2.5. Social Cost of Carbon

The social cost of carbon (Pizer et al., 2014; Ricke et al., 2018) is the economic value of an additional metric ton of CO<sub>2</sub> 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, the Policy Analysis of the Greenhouse Effect (Hope, 2006), and the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) (Waldhoff et al., 2014) models are used to estimate this metric (Cai & Lontzek, 2019; Nordhaus, 2017) which is still a subject of heated debate as its value remains largely uncertain (Daniel et al., 2019; Pindyck, 2017, 2019; Wang et al., 2019). It is computed as the loss of consumption resulting from a pulse in emission at a given time (Anthoff et al., 2009; Ricke et al., 2018) and it is reported in USD tCO<sub>2</sub><sup>−1</sup>.

In particular, we obtain it as the difference between two consumption pathways. The first pathway is the consumption obtained by simulating the selected climate policy. The second pathway is obtained by simulating the same policy and adding a unit emission in the year for which we want to compute it. The two consumption trajectories are discounted using the real interest rate. The difference in discounted consumption is then divided by the number of emissions used in the pulse, meaning that we account for the year time steps, which results in a total addition of 5.0 GtCO<sub>2</sub>, to obtain the social cost of carbon value. This can be described using the following equation:

$$SCC(t) = \frac{\sum_{\tau=t}^H \frac{C_{\tau} - C_{pulse,\tau}}{(1 + r_{i,\tau-t})}}{\sum_{\tau=1}^5 E_{pulse,t}} \quad (15a)$$

where  $C_{\tau}$  and  $C_{pulse,\tau}$  are the consumption obtained by simulating a specific policy in the model with no modifications and adding a pulse in emission at time  $t$ , respectively.  $r_{i,t}$  is the real interest rate at time  $t$  and  $E_{pulse,t}$  is the emission pulse, summed over the length of the time step to account for the total emissions added to the simulation. It is important to note that the decisions are left free to adjust after the pulse in emissions for SACPs. In contrast, this is not possible for static ones as it would require solving an additional multi-objective optimization problem for each time step and each scenario examined.

### 3. Results

#### 3.1. Climate Adaptation Leads to a Resurgence of Conflict Between Climate Policy Objectives

Explicit uncertainty and adaptation are two fundamental aspects overlooked in recent cost-benefit analysis proving the economic optimality of the Paris Agreement (Glanemann et al., 2020; Hänsel et al., 2020). We measure the effect of these two factors by reporting global mean surface temperature and CO<sub>2</sub> emissions under different modeling assumptions. We consider the problem of climate policy design under deterministic conditions with and without explicit adaptation. Then, we explore how policy changes when we explicitly consider uncertainty by accounting again for implicit and explicit adaptation. We then reevaluate the solutions over a range of scenarios (see Section 2 and Supporting Information S1) to examine their behavior which is reported in Figure 1. A deterministic decision-making model without explicit adaptation (Figure 1a)—equivalent to the latest cost-benefit analysis results (Hänsel et al., 2020) and starting point of this analysis—results in median temperature overshooting the 2°C around 2050 when reevaluated under uncertainty. If explicit adaptation is considered under the deterministic approach (Figure 1b), the median temperature can reach 3°C. Designing climate policy accounting for uncertainty with implicit adaptation (Figure 1c) reduces the conflict as overshoot is strongly reduced and the median temperature peaks around 1.8°C. Yet, even under uncertainty, explicit adaptation causes the conflict between maximizing economic welfare and complying with the Paris Agreement (Figure 1d).

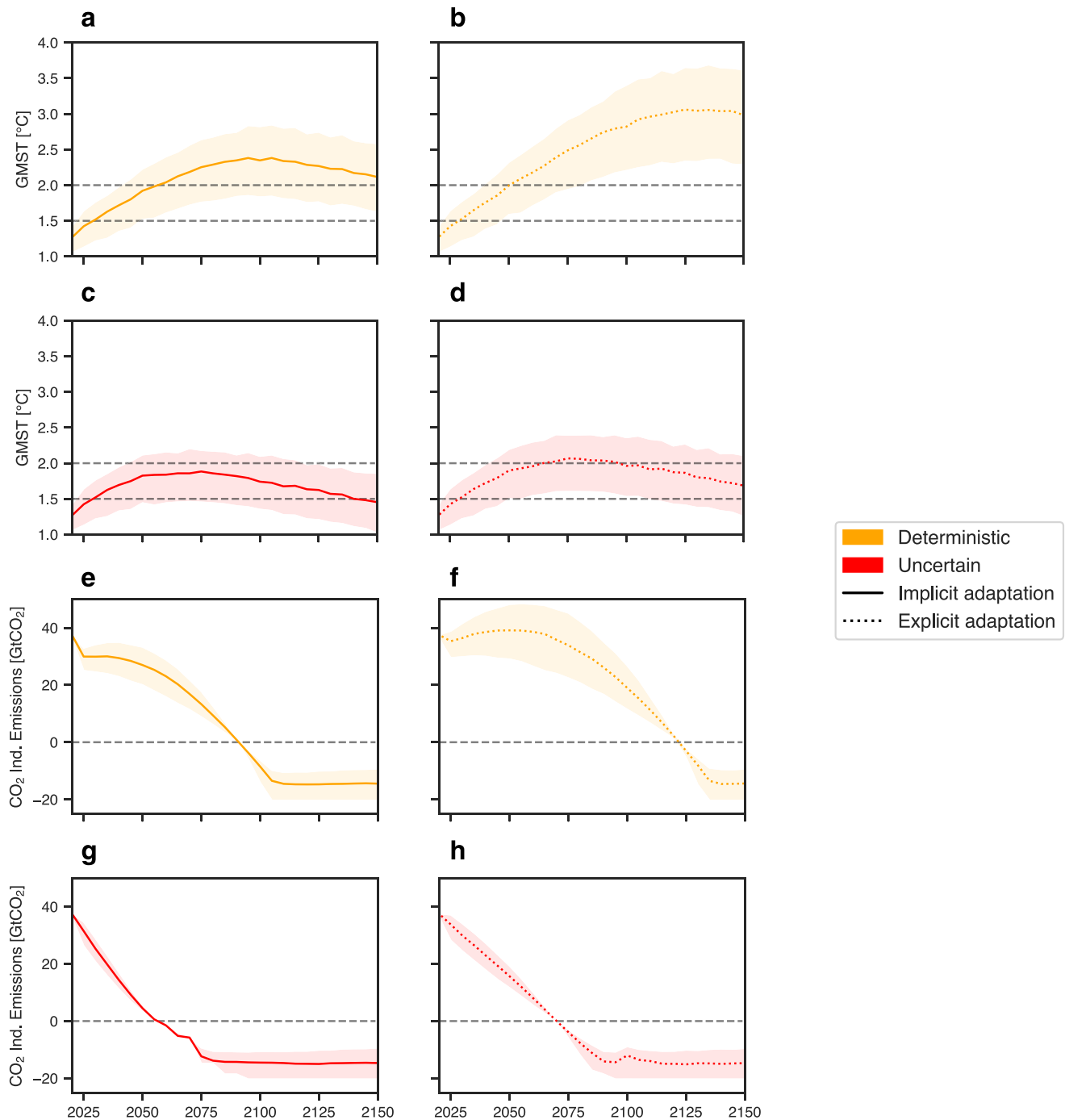
The rationale behind these temperature outcomes lies in the actions that the decision-maker can consider to design the climate policy. Indeed, if adaptation is not explicitly available, high climate impacts can only be reduced via additional mitigation, as visible in Figures 1e–1g. On the other hand, with explicit adaptation, mitigation can be postponed as adaptation reduces future impacts (Figures 1e–1g). Even under strong uncertainty, much higher investments in adaptation are preferred over early mitigation resulting in high emissions, high temperature, and overshoot of the 2°C threshold (Figures 1f–1h).

#### 3.2. Self-Adaptive Multi-Objective Climate Policies Reduce the Conflicts

We take advantage of multi-objective optimization to consider simultaneously different climate policy objectives: maximization of welfare, minimization of the probability of overshooting 2°C, minimization of warming above 2°C, and minimization of the NPV of climate damages, mitigation costs, and adaptation costs.

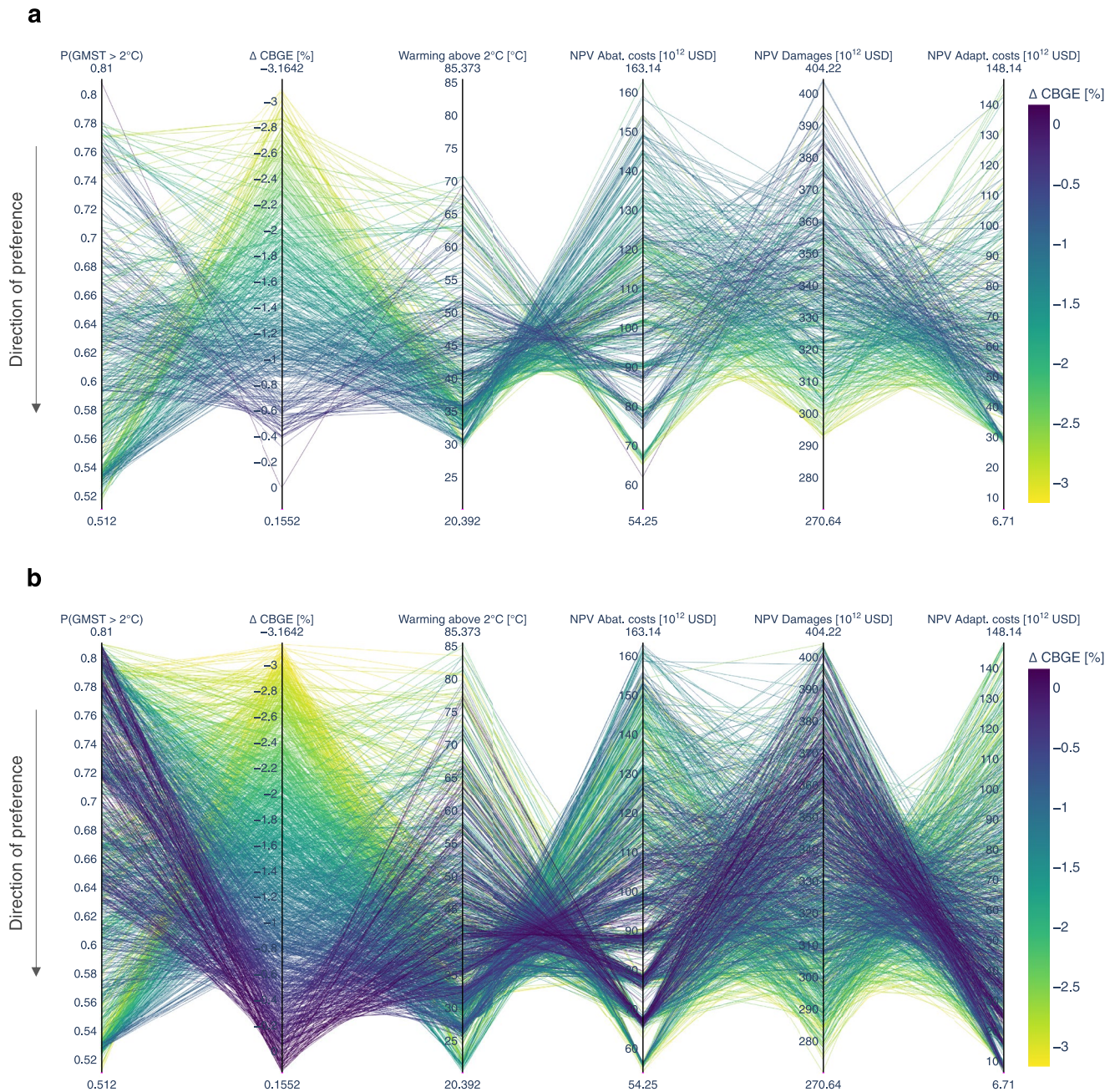
First, we consider the potential of these methods using multi-objective static climate policies (see Section 2), in line with previous research in this direction (Garner et al., 2016; Marangoni et al., 2021). The solution to this optimization problem is a set of Pareto-optimal solutions for which improving one objective leads to a degradation of at least one of the other objectives. The full representation of solutions across the six dimensions is reported





**Figure 1.** Implications for Paris Agreement compliance using the traditional static welfare maximization decision-making model. We report global mean surface temperature (GMST) trajectories under four decision-making models: (a) deterministic with implicit adaptation; (b) deterministic with explicit adaptation; (c) uncertain with implicit adaptation; (d) uncertain with explicit adaptation. Similarly, we report CO<sub>2</sub> industrial emission trajectories for the same conditions in panels e–h. Temperature and emissions trajectories are reported using the median and 66% probability intervals. Explicit adaptation modeling delays mitigation while uncertainty makes lower temperatures economically favorable. Yet, including these two additional components leads to a resurgence of the conflict between economic optimality and climate stabilization below the 2°C threshold.

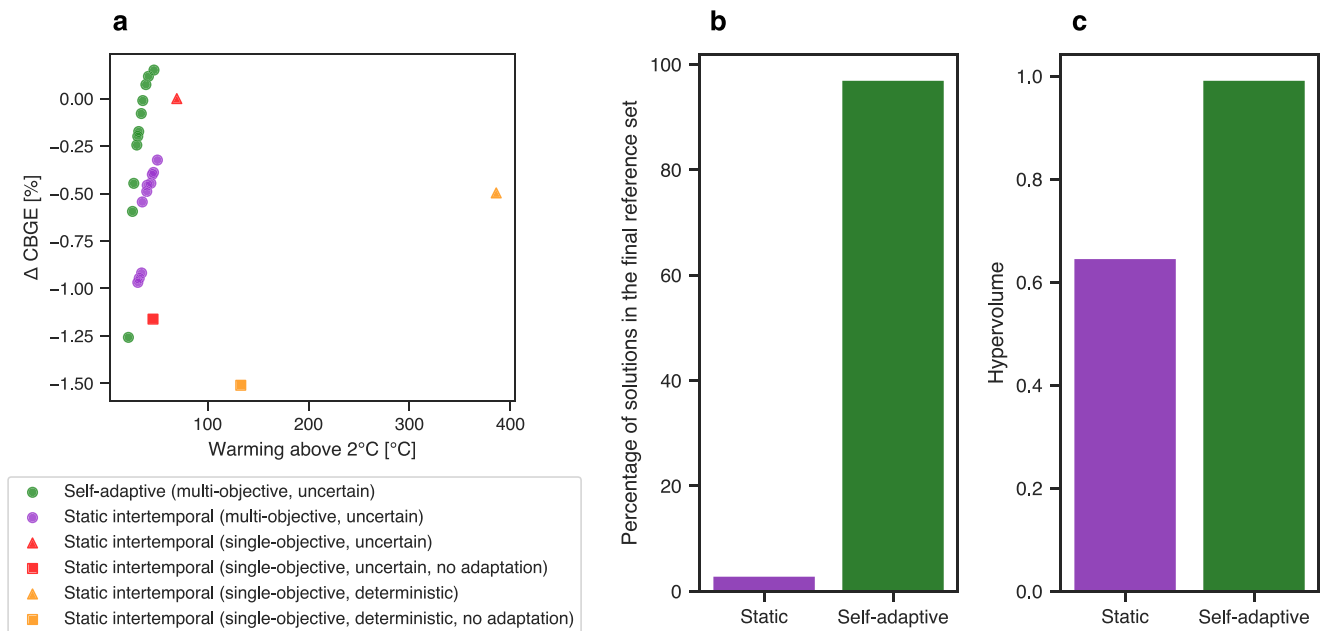
in Figure 2a. Here, we focus on the conflict between warming above 2°C and welfare maximization recast as the change in CBGE (Anthoff & Tol, 2009). CBGE measures the reduced stream of consumption needed to implement the proposed climate policy, using the solution maximizing welfare under uncertainty and explicit adaptation as a reference. In Figure 3a, solutions are selected based on their Pareto-optimality with respect to these



**Figure 2.** Parallel coordinates plot reporting the full range of solutions obtained for (a) static intertemporal and (b) self-adaptive multi-objective climate policies. Vertical axes show the six objectives considered in the optimization. For each of those, the optimal value is found at the bottom. Therefore, a line crossing all the axes at their bottom end would represent a utopic climate policy where conflicts between objectives do not exist. Self-adaptive climate policies reach the lowest value in each vertical axis and display lower intersection between lines, meaning that the conflict between the objectives is smaller than with static intertemporal policies.

two objectives: multi-objective static climate policies can explore the space of trade-offs but balancing these objectives requires strong choices as the value of the economic objective decreases remarkably when trying to reduce warming above 2°C.

Second, we show that by adopting a self-adaptive multi-objective decision-making model (see Section 2) it is possible to reduce the conflict as the obtained Pareto front moves toward a smaller or even positive difference in CBGE and lower warming above 2°C, that is, the direction of preference for both objectives (see Figure 3a). In this case, the solution is a set of Pareto-optimal control policies that map the observed state of the socio-climatic

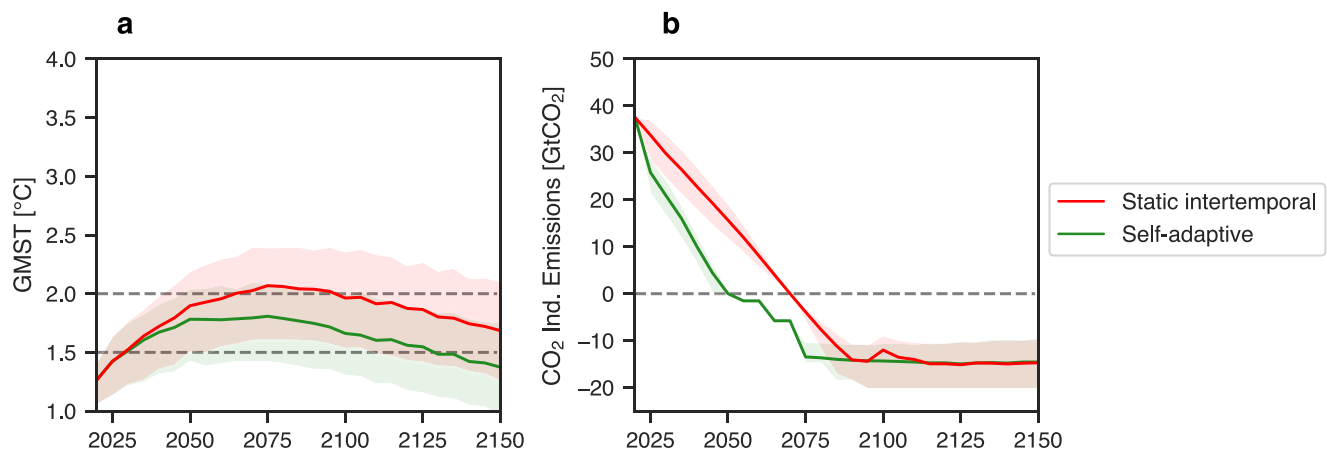


**Figure 3.** Self-adaptive climate policies cover more consistently the space of the objectives than static policies and reduce the conflict between economic and other climate policy objectives: (a) space of the objectives considering welfare maximization (reported as difference in Certainty Balanced Growth Equivalent (CBGE)) and minimization of warming above 2°C; (b) percentage of solutions selected after merging and Pareto sorting all the solutions available; and (c) hypervolume metrics computed for the two types of policies.

system (i.e., the global economic capital stock, the magnitude of observed climate damages, the atmospheric temperature, the CO<sub>2</sub> concentration, and the adaptation capital stock) into the next action to be taken (i.e., fraction of emissions to be controlled, savings rate of the global economy, investment in short-term and long-term adaptation measures). This allows decision-makers to adjust the strategy and respond to uncertainty based on state information—that is, the dynamic variables that influence the system's evolution to the next step—where knowledge about the system accumulates as this evolves during each simulation. This methodology yields an improved representation of the actual decision-making process as decisions will inevitably adapt to the emergence of new information about the state of the socio-climatic system. The same range of warming above 2°C considered by the static single-objective climate policy can be reached with welfare similar to that of a welfare-maximizing solution, strongly reducing the conflict between these two objectives. In particular, with the same level of welfare, SACPs reduce warming above 2°C by 30%–50%. Analogously, for the lower warming achievable with static climate policies, self-adaptive reduces the consumption loss by 0.4%–0.6%, making it almost comparable with the reference value. It is also interesting to note that the welfare-maximizing solution % °reduces the average warming above 2°C by 30%. If we examine the six objectives all at once, SACPs dominate static policies: almost all of them are selected when merging all solutions to compute a final reference set using Pareto sorting (Figure 3b). Similarly, the ability to more consistently explore the full range of Pareto-optimal solutions is computed using the hypervolume metric (While et al., 2011; Zitzler et al., 2000): SACPs outperform static intertemporal climate policies, i.e., the ensemble of SACPs is closer to an ideal solution achieving maximum performance across all the objectives.

### 3.3. Flexible Balancing of Mitigation and Adaptation Strategies

SACPs reduce the conflict between the objectives as climate decisions are adjusted to each scenario simulated. The different components of the total cost are reorganized to achieve satisfactory performance across all objectives. In other words, starting from a similar value of any cost metric, SACPs combine economic and temperature objectives more efficiently than static policies, as reported in Figure 2. Using these panels static and self-adaptive policies can be compared to examine their respective ability to manage trade-offs between the different objectives. Indeed, self-adaptive policies reach a lower point in all axes considered, reporting better solutions for each single-objective perspective represented by each axis. Furthermore, intersections from one axis to another are



**Figure 4.** (a) Global mean surface temperature (GMST) and (b) CO<sub>2</sub> emissions trajectories for the single-objective welfare-maximizing static climate policy (red) and the selected compromise self-adaptive policy (green). The selected self-adaptive policy, with a small reduction in certainty balanced growth equivalent ( $-0.06\%$ ), implements faster emission reduction and keeps the median temperature well below  $2^{\circ}\text{C}$ , also including  $1.5^{\circ}\text{C}$  in the uncertainty range. The solid line represents the mean, while the uncertainty range reports the 66% probability interval.

always lower in the case of self-adaptive policies, pointing toward less pronounced conflicts between all of the objectives considered.

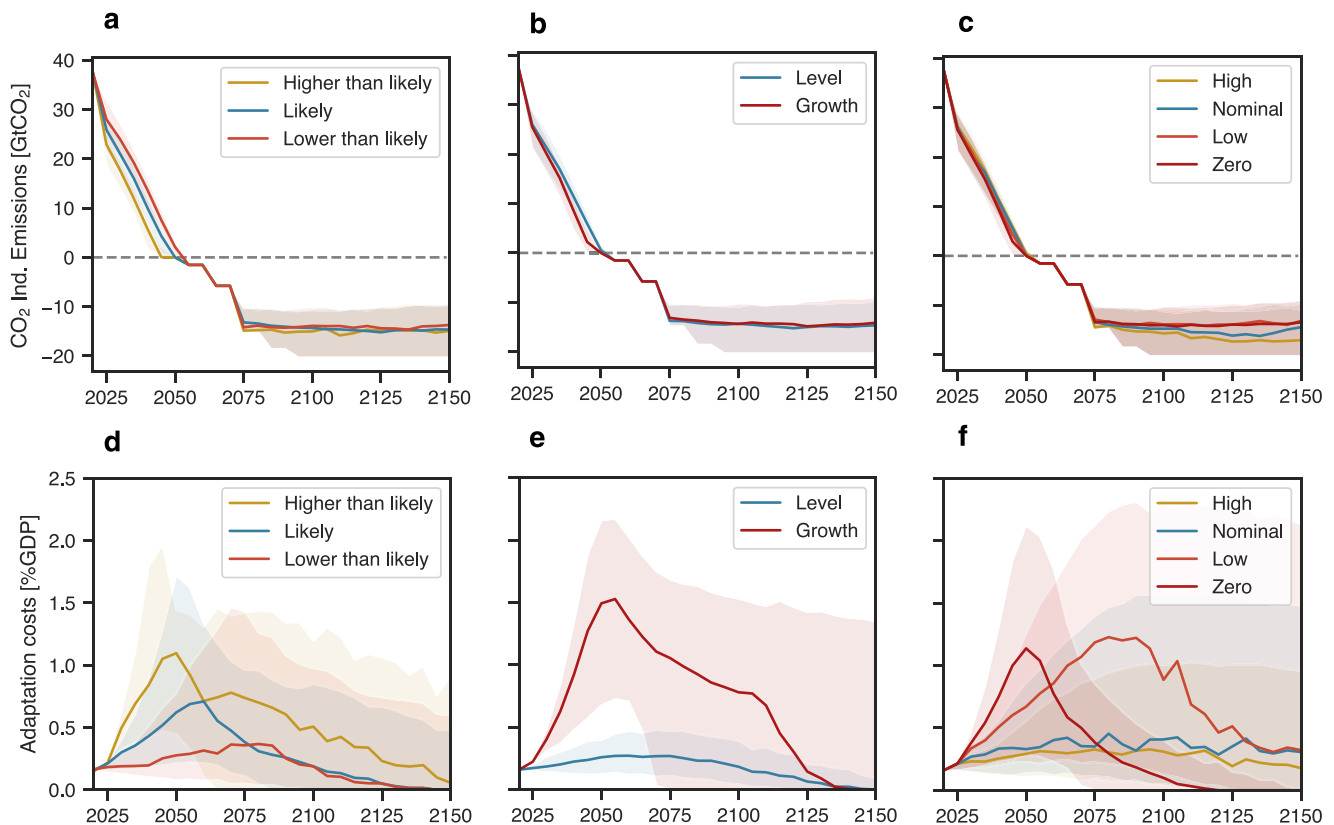
To understand the reason behind this progress, we explore the variability of mitigation and adaptation actions for a selected self-adaptive compromise climate policy that reduces the maximum distance for the maximum value of each objective while guaranteeing welfare comparable to that of the welfare-maximizing static climate policy. In particular, the compromise self-adaptive climate policy is found first discarding solutions resulting in more than  $0.5\%$  CBGE loss with respect to the reference static climate policy, and then ranking the remaining solutions based on their performance in welfare, the probability of remaining below  $2^{\circ}\text{C}$ , warming above  $2^{\circ}\text{C}$ , and the NPV of climate damages. The solution with the highest lowest ranking across these four metrics is used.

The trajectories of the selected climate policy are reported in Figure 4 and compared with the single-objective welfare-maximizing climate policy designed under uncertainty and explicit adaptation modeling. The selected self-adaptive policy reduces emissions very fast, going to zero between 2045 and shortly after 2050, keeping the median temperature well below  $2^{\circ}\text{C}$  and including  $1.5^{\circ}\text{C}$  in the 66% probability interval. This is compared with the trajectories of the single-objective static policy considering uncertainty and explicit adaptation. The difference in welfare is negligible between the two solutions, with a delta in CBGE of  $0.06\%$ .

The variability of mitigation and adaptation decisions is examined with respect to three of the many uncertainties affecting the model: Transient Climate Response (TCR), climate damages specification, and adaptation efficiency. In Figures 5a–5c, we report the variability of CO<sub>2</sub> emissions based on different levels of these uncertainties. As expected, if the TCR is higher than the likely range, emission reduction effort is increased in trying to cope with this unfavorable scenario, reaching zero CO<sub>2</sub> emissions in 2045 on average. On the other hand, when low TCR is observed, emissions decline over a longer horizon, reaching zero CO<sub>2</sub> emissions after 2050. When growth-type climate damages are observed, stronger emission reduction takes place, but the median year of zero CO<sub>2</sub> emissions is only slightly anticipated. Finally, also adaptation efficiency plays a role in emission reduction: when low or even zero adaptation efficiency is observed, emissions are reduced faster. Yet, zero CO<sub>2</sub> emissions year is not affected.

In Figures 5d–5f instead, we report the variability of adaptation expenses based on the same uncertainties. As previously noticed, adaptation is increased earlier in the presence of higher TCR values, while it changes are growing grew more slowly when TCR is lower and less needed. As for the damages, adaptation efficiency is higher to cope with increased impacts when growth-type damages are simulated. Finally, higher adaptation expenses are observed when adaptation efficiency is low, and vice versa, lower adaptation expenditures are observed with high adaptation efficiency. For zero adaptation efficiency, the model initially invests significant resources into adaptation, yet, after realizing that this measure is not working as expected, the adaptation effort is reduced to zero. This is due to the partial observability of adaptation efficiency, which is masked by climate damage specifications





**Figure 5.** Variability of mitigation and adaptation decisions in the selected self-adaptive climate policy. Variability of emissions reported for (a) levels of transient climate response (TCR), (b) climate damages specification, and (c) adaptation efficiency. Variability of adaptation expenditure reported for (d) levels of TCR, (e) climate damages specification, and (f) adaptation efficiency. The solid line represents the mean while the uncertainty range reports the 66% probability interval.

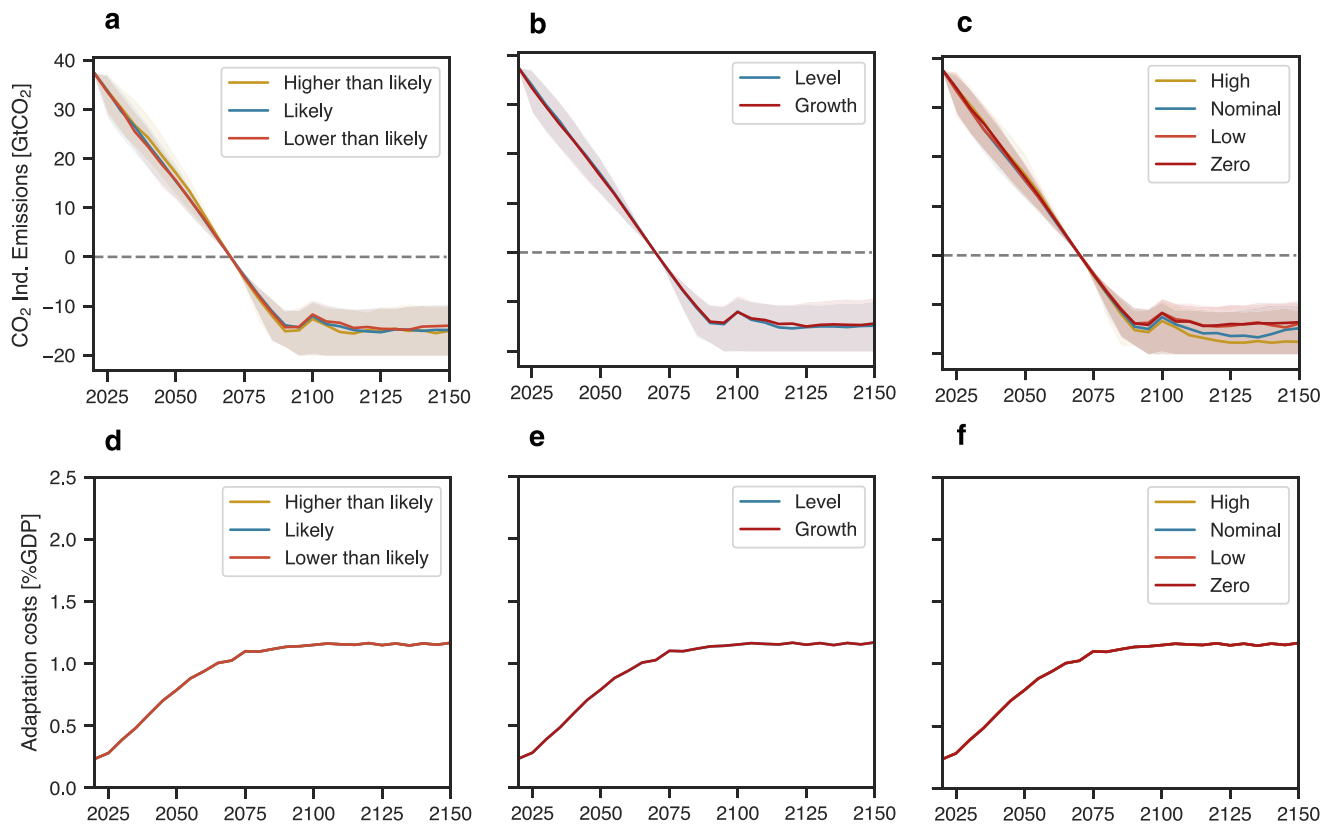
and other uncertainties making it hard to understand the efficiency level of adaptation measures. Therefore, it is necessary to explore the different strategies to find the most appropriate balance of adaptation and mitigation for each simulated scenario. Adaptation is generally reduced in the long term as impacts and temperatures decrease as a result of negative emissions.

The significant variability of adaptation strategies is emphasized by the much more compact uncertainty about the emissions reduction pathway. Nonetheless, this is expected as it is well understood that emissions need to decline fast to halt temperature increase, independently of the scenario. On the other hand, since large uncertainty about climate impacts and adaptation potential remains, adequate implementation of climate adaptation is key to ensuring the satisfaction of multiple objectives. The strategies developed to cope with such uncertainty with a coherent approach to reinvigorate the importance of focusing on adaptation science (Sobel, 2021).

The ability to adjust mitigation and adaptation decisions of the selected self-adaptive policy can be further appreciated by comparing the variability discussed above and reported in Figure 5 with the variability of the static climate policy, which is driven only by the inherent model uncertainty, reported in Figure 6.

### 3.4. Implications for the Social Cost of Carbon and Multi-Objective Cost of Climate Inaction

The shift to self-adaptive decision-making implies that the socio-economic model component is left free to adjust decisions after the pulse in emission. Consequently, the median social cost of carbon for the Pareto-optimal solutions previously examined in Figure 3a and its associated uncertainty is lower for SACP as reported in Figure 7. While the value of the median social cost of carbon can change depending on the selected compromise policy, for any given level of welfare or expected warming above 2°C, the social cost of carbon of the self-adaptive policies remain lower, between 150 USD tCO<sub>2</sub><sup>-1</sup> and 200 USD tCO<sub>2</sub><sup>-1</sup> in 2020 and from 160 USD tCO<sub>2</sub><sup>-1</sup> to 230 USD tCO<sub>2</sub><sup>-1</sup>



**Figure 6.** Variability of mitigation and adaptation decision in the static climate policy maximizing welfare under uncertainty and explicit adaptation modeling. Variability of emissions under (a) different levels of transient climate response (TCR), (b) different climate damages specifications, and (c) different adaptation efficiency values. Variability of adaptation expenditure under (d) different levels of TCR, (e) different climate damage specifications, and (f) different adaptation efficiency values. The solid line represents the mean while the uncertainty range reports the 66% probability interval.

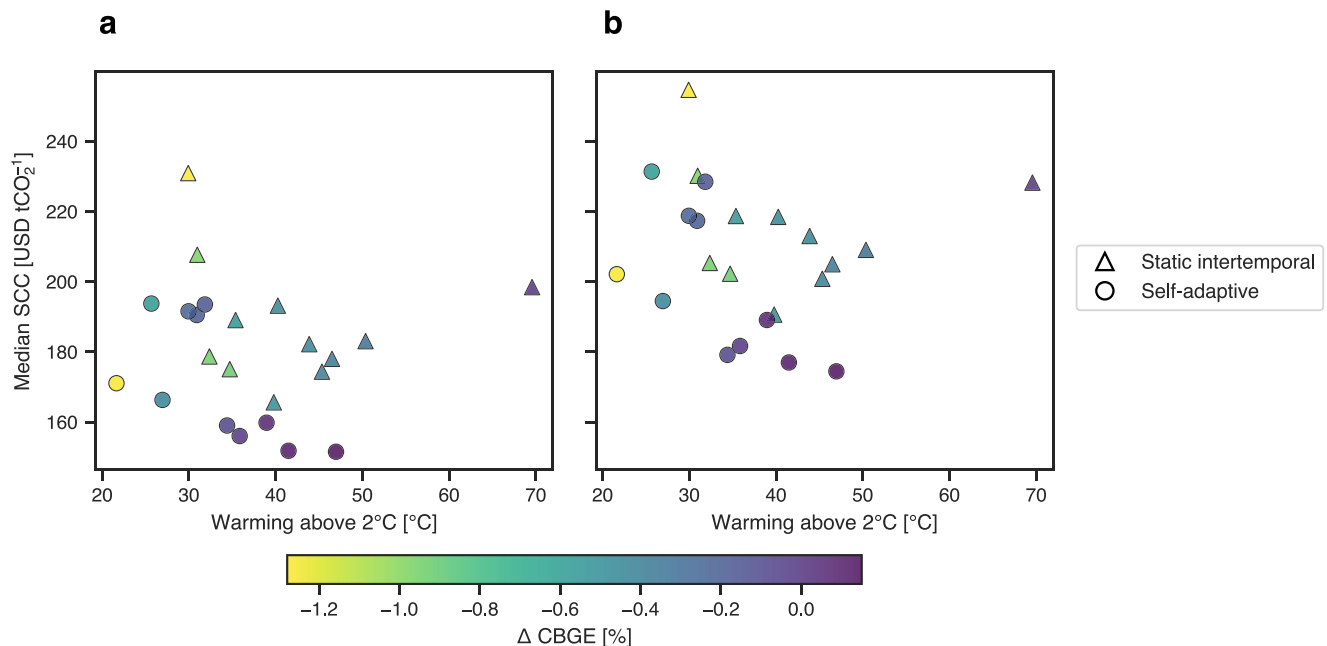
in 2030. On the other hand, static policies produce a cost of 160 USD  $\text{tCO}_2^{-1}$  to 230 USD  $\text{tCO}_2^{-1}$  in 2020 and 190 USD  $\text{tCO}_2^{-1}$  to 255 USD  $\text{tCO}_2^{-1}$  in 2030.

While economic loss due to additional emissions can be estimated using the social cost of carbon, the ability to harmonize the different economic and temperature targets can be severely reduced by inaction. To examine this aspect we run the same policies examined in Figure 3 constraining emissions to remain at 2020 levels for 5 and 10 more years. In Figure 8a, we report the performance of the policies selected by performing a Pareto sorting over the two objectives to examine how rapidly the ability to limit warming above 2°C is degraded as current emissions are prolonged. While all the policies degrade, the self-adaptive ones are still better than the static ones. Yet, the conflict increases under all the decision-making perspectives, and solutions considering low warming become dominated. Additionally, we analyze how inaction affects the six objectives reporting the hypervolume of the original policies—proposing early climate action—and of the same policies affected by 5 and 10-year inaction in Figures 8b–8d. As current emissions are prolonged, the ability to harmonize many objectives is lost rapidly. The loss is larger in the first 5 years than over a longer time horizon, highlighting the significance of mitigation in the short term. Additionally, inaction over 10 years would squander all the improvements associated with the self-adaptive policies reducing their hypervolume to the static policies' current value.

#### 4. Conclusions

Recently, climate economics has reconciled welfare-maximizing cost-benefit analysis set by the Paris Agreement in 2015 (Glanemann et al., 2020; Hänsel et al., 2020). Yet, removing some major assumptions on which these models are based undermines such results. Indeed, climate adaptation, only implicitly included in those recent





**Figure 7.** Median Social Cost of Carbon (SCC) values for the static and self-adaptive climate policies (SACPs) (a) in 2020 and (b) in 2030. SACPs provide lower values and variability across the Pareto front, considering only welfare and warming above 2°C. This result is a consequence of the adjustment of decisions after the pulse in emissions.

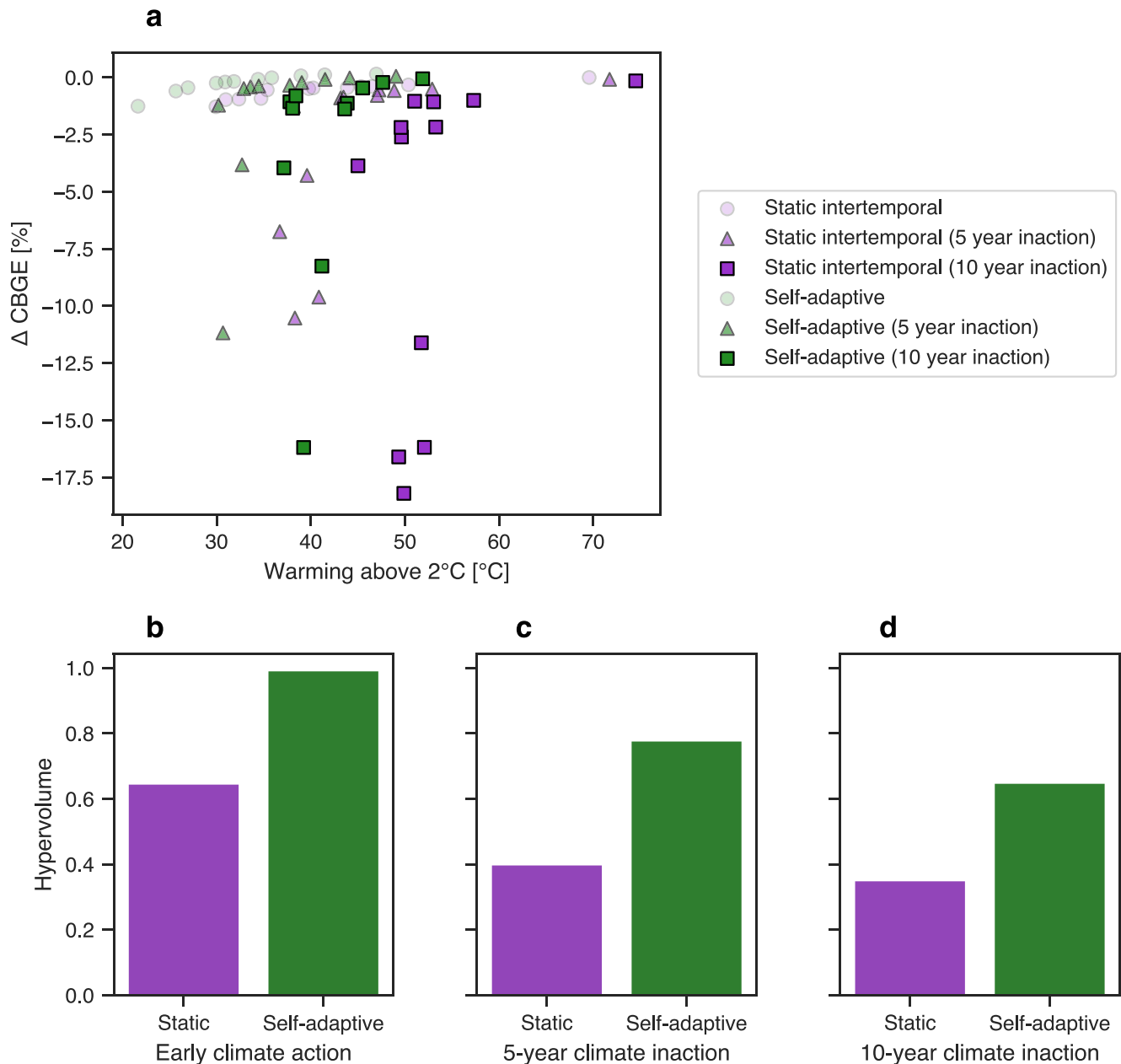
assessments (Füssel, 2010), together with explicit consideration of uncertainty and of the corresponding interacting and self-adaptive behavior of the decision-maker, have been overlooked and require to be examined jointly.

We confirm previous research results (Agrawala, Bosello, Carraro, De Bruin et al., 2011; Bahn et al., 2019; De Bruin et al., 2009) showing that introducing adaptation in the cost-benefit IAM DICE produces a climate policy leaning toward adaptation resulting in conflict between the economic and the temperature objective. Similarly, it is well known in the scientific literature that accounting for uncertainty results in more stringent mitigation, especially when adaptation is not explicitly modeled (Cai et al., 2016; Cai & Lontzek, 2019; Ekholm, 2018; Felgenhauer & De Bruin, 2009; Jensen & Traeger, 2014). Yet, the potential of adaptation dominates the two when these two components are analyzed jointly which leads to a resurgence of conflicts between environmental and economic objectives.

By adopting a self-adaptive and multi-objective decision-making model, we show that this conflict can be mitigated. Indeed, a multi-objective design delivers good performance on many climate policy targets without significant losses in the traditionally only metric assessed, utilitarian welfare. The improvement derives from the self-adaptive multi-objective climate policies' ability to adjust mitigation and adaptation decisions over time to react to the unfolding of the coupled socio-climatic model. Since they manage better adaptation costs in the long term, more economic resources are available to increase mitigation effort in the short-term. As a result, they keep temperatures within safer levels, which is also the most robust strategy to reduce climate damages in the long-term.

Finally, we examine the implications of different decision-making models for the social cost of carbon and for the ability to manage trade-offs between climate objectives after an initial delay in climate action. The multi-objective adaptive climate policies provide a general reduction of the social cost of carbon, resulting from their ability to tailor the climate strategy to each future state of the world. Nevertheless, early mitigation is crucial to ensure effective management of the trade-offs between multiple climate objectives since any delay would only intensify the conflicts between temperature and economic objectives.

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



**Figure 8.** The cost of inaction with respect to welfare and warming above 2°C. As 2020 emissions are prolonged for 5 or 10 years more, the conflicts between the objectives are stronger and solutions enabling low warming are lost as they become dominated. Rapid climate action warrants more space for harmonization of climate policy objectives.

reflect the different interests involved in the decision-making process: the economic point of view has to be harmonized with environmental, social and political targets. To overcome this weaknesses, we present an instrument to improve climate decision-making by leveraging information collected during the simulation to balance trade-offs between many climate objectives. Expanding the number of dimensions we use to evaluate the performance of climate policies is key to reduce conflict between these objectives and to foster a clear and open debate over the political nature of the alternatives considered.

## Data Availability Statement

The simulation model, the characterization of uncertainties, the calibration of the surrogate econometric damages model, and the simulation version of the FAIR climate model are available together with the optimization outputs and script for figures at the following repository: <https://doi.org/10.5281/zenodo.6820076> (Carlino, 2022).

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