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Who turns the global thermostat and by how much?

Wilfried Rickels^{a,*}, Martin F. Quaas^{a,b}, Katharine Ricke^c, Johannes Quaas^b,
Juan Moreno-Cruz^d, Sjak Smulders^e

^a Kiel Institute for the World Economy, 24105 Kiel, Germany

^b Universität Leipzig, 04103 Leipzig, Germany

^c UC San Diego, La Jolla, CA 92093-0519, USA

^d University of Waterloo, Waterloo, Ontario, N2L3G1, Canada

^e Tilburg University, 5037 AB Tilburg, Netherlands

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ABSTRACT

Increasing attention is being given to the option of engineering the climate via Solar Radiation Management (SRM) as a potential component in future climate policies. We set up a quantitative model to analyze efficient levels of SRM deployment against the climatic and economic background conditions projected by the various Shared Socioeconomic Pathways (SSPs) baseline scenarios for the year 2050. The model combines three features of the data: i) SRM deployment is regionally uneven in the way it affects grid-cell temperature and precipitation, ii) temperature and precipitation affect Gross Value Added (GVA) at the grid-cell level and the effect for both takes the form of an inverted U-shape relationship, implying that optimal temperature and precipitation levels with respect to output do exist, and iii) different assumptions about economic growth and its distribution over regions, as projected by the SSPs, increase the relative share of global GVA for currently rather poor countries with high average temperatures. We find that in global terms, economically efficient levels of SRM are affected more by region-specific economic growth projections than by regional climate-change impacts. Globally, the economically efficient SRM level is proportional to the (global) GVA-weighted mean temperature increase, which varies considerably according to the various growth projections (for equal climatic background conditions). Achieving the optimal temperature in each scenario is constrained by the influence of SRM on precipitation.

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1. Introduction

Engineering the climate via Solar Radiation Management (SRM) has received increasing attention as a potential scenario for future climate change policies in particular because SRM technologies like stratospheric aerosol injection have prospects of altering the global mean temperature at rather low operational cost and almost instantaneously, i.e. in the time-scale of a year (Keith, 2000; Crutzen, 2006; Lenton and Vaughan, 2009). However, projections indicate that SRM deployment will change climate variables like temperature and precipitation in a regionally uneven way differing from the effects of climate change (Allen and Ingram, 2002; Trenberth and Dai, 2007; Rasch et al., 2009; Ricke et al., 2010; Ricke et al., 2012). Furthermore, SRM is expected to involve various inherent side effects, ranging from reduced occurrence of blue skies to the non-mitigation of carbon-

related impacts (e.g., Robock et al., 2008; Robock et al., 2009). This implies that any decision about SRM deployment will involve economic trade-offs as well as various social, political, legal, and ethical considerations (Barrett, 2014; Klepper and Rickels, 2014). Economic reasoning may be particularly relevant in the decision on how much SRM should be deployed and accordingly on the degree to which global mean temperature is reduced.

The relation between economic output and temperature can be described by an inverted U-shaped function suggesting that some economically “optimal” climate exists (Nordhaus, 2006; Tol, 2018, 2019). Climate change shifts the countries’ distribution along the optimal temperature curve to the right, so that “cold” countries move closer to climate optimum, while “hot” countries move further away from it. SRM would shift countries to the left and thus have the opposite effect: “cold” countries move farther away from the climate optimum, while “hot” countries move closer to it. Accordingly, countries have different preferences regarding the level of SRM to be deployed. The present paper discusses SRM deployment scenarios that can be expected given heterogeneous economic interests with regard to climate change.

* Corresponding author.

E-mail address: wilfried.rickels@ifw-kiel.de (W. Rickels).

If the operational costs of SRM are fairly low, the pure non-cooperative Nash equilibrium outcome would be that the country with the strongest interest in cooling the climate would apply a high level of SRM to adjust the global temperature to their preferred level (Barrett, 2008, 2014). In contrast to the free-rider problem posed by climate-change mitigation, the actual governance challenge associated with SRM deployment thus becomes a free-driver problem (Weitzman, 2015). Assuming the existence of an “optimal” climate with respect to economic activity, several countries might even have an incentive to “overcool” the global climate in order to get their individual regional climate closer to the optimal climate. Accordingly, not only climate-change winners but also other countries would face an overprovision of SRM deployment (Moreno-Cruz, 2015; Weitzman, 2015).

However, following the international logic of multilateralism, Horton (2011) argues that given the various retaliation channels in combination with the rules of international law, it is rather unlikely that SRM measures would be applied unilaterally regardless of other countries' interests. In the same vein, Parson and Ernst (2013) argue that in terms of financial, technological, logistical, and military strength, only a very small number of states would be capable of upholding SRM against international opposition, implying at the same time that countries without coalition commitments can be expected to be capable of imposing externalities on coalition members. Accordingly, it appears unlikely that independently of agreements and against international opposition, countries with a preference for the coolest possible climate would be able to impose their preferred degree of SRM without compensating SRM losers.

In addition, SRM deployment influences not only temperature but also other climate variables like precipitation. Increasing temperatures resulting from increased GHG concentration also influence the hydrological cycle, and increased GHG concentration itself influences the hydrological cycle directly. Temperature-induced influence increases the intensity of the hydrological cycle, while GHG-induced influence reduces it (Allen and Ingram, 2002). The temperature influence dominates, implying that increased GHG concentration will tend to increase mean global precipitation. However, the precipitation increase is less than proportional to the temperature increase. Consequently, SRM deployment cannot control temperature and precipitation simultaneously because fully compensating for the increase in mean temperature will actually overcompensate for the increase in mean precipitation (e.g., Ricke et al., 2012), resulting in a drop in mean precipitation. Also, while GHG-induced radiative forcing is more or less equal across the globe, negative radiative forcing of SRM measures would be strongest in locations with high irradiation. As a result, temperature and precipitation react differently to SRM depending on the region in question (e.g., Trenberth and Dai, 2007; Rasch et al., 2009; Ricke et al., 2010; Ferraro et al., 2014).

In this paper we propose a stylized model characterizing the level of SRM deployment that is globally efficient, i.e. that maximizes global gross value added (GVA). We find that this is the level of SRM that minimizes the global GVA-weighted average gap between the country-specific actual climate on the one hand and its output-maximizing climate on the other. The (regional) climate is measured by both mean temperature and mean precipitation. Since regional variation in economic output is much stronger than variations in local temperature and precipitation sensitivity to SRM, the gaps in high-income locations are the main drivers behind the globally efficient SRM level. We quantify these effects for hypothetical SRM deployment in the middle of the century. In our analysis we combine data on the influence of SRM on grid-cell temperature and precipitation derived from earth-system model simulations (Ricke et al., 2012), data on the influence of temperature and precipitation on grid-cell gross value added from the G-Econ database (Nordhaus, 2006), and data on the future distribution of economic output from the SSP

database for different growth assumptions (Cuaresma, 2017; Dellink et al., 2017). Our analysis shows that the globally efficient level of SRM deployment strongly depends on the background conditions projected under the five baseline scenarios of the Shared Socioeconomic Pathways (SSP).

Our work contributes to the literature analyzing challenges to SRM governance. Moreno-Cruz et al. (2012) and Ricke et al. (2013) take SRM's regionally uneven effect on temperature and precipitation into account and investigate the optimal level of SRM deployment. However, both assume that there are no climate-change winners and that all countries face climate damages associated with deviations in temperature or precipitation from the country-specific preindustrial level. Accordingly, they find that there is a degree of SRM that reduces climate damages for all countries, albeit in different proportions. More specifically, Moreno-Cruz et al. (2012) investigate the level of SRM that would bring a Pareto improvement over and against the case without SRM, while Ricke et al. (2013) investigate the SRM level that would be optimal for different coalitions of countries.

By contrast, Tol's (2016) starting point—an inverted U-shape relationship between economic output and temperature—implies that some countries would gain from climate change. He investigates the decision on optimal global temperature as an analogy for SRM deployment. His analysis is based on a meta-analysis of climate change impact functions derived from integrated assessment models (Tol, 2018, 2019). In his analysis climate change has very different impacts on different countries, and there would be disagreement about the desired level of SRM deployment, also implying that SRM deployment cannot represent a Pareto optimum. He derives a Kaldor-Hicks efficient global optimal temperature level, requiring compensation for countries that prefer a lower level of temperature and suggests income transfers for that purpose. Like Tol (2016), we derive the globally efficient solution in accordance with the Kaldor-Hicks criterion. The added value of our contribution lies in the fact that we explicitly take into account the regionally uneven influence of SRM on temperature and precipitation, which shows in particular that the influence of SRM on precipitation leads to a trade-off between improving on precipitation and coming closer to the global “optimal” temperature. Tol (2016) also investigates country-specific incentives and contributions deriving willingness-to-pay and willingness-to-accept estimates for changing the temperature from the optimal country-specific temperature levels. This derivation operationalizes the Shapley value (Shapley, 1953) and thus provides information on country-specific payments and compensations. We take a different line, deriving country-specific contributions under the Vickrey-Clarke-Groves (VCG) mechanism (Vickrey, 1961; Clarke, 1971; Groves and Loeb, 1975). We rather focus on the country-specific incentives to join a global SRM agreement in terms of paying for turning the global thermostat more into the preferred direction. Even if the optimal country-specific climate would be private information, the VCG mechanism would lead to the efficient solution as truthfulness is a dominant strategy (though at the cost of losing the budget-balance feature).

The paper is structured as follows: Section 2 introduces our decision framework for global SRM deployment and explains the calibration for the quantitative illustration. Section 3 presents our results, discussing the efficient global level of SRM deployment (Section 3.1), the individual country incentives (Section 3.2), the participation gains in a global agreement on SRM deployment (Section 3.3), and the implications for coalition formation (Section 3.4). Section 4 concludes.

2. Methods

2.1. Model

To analyze country-specific interests regarding the level of SRM deployment, we assume that countries will prefer a climate that benefits their current economic output. Global economic efficiency thus requires

maximizing global economic output. One appealing approach in normative terms would be to maximize some social-welfare function embodying concerns for global economic justice. If international transfers of economic resources are freely possible and the welfare function satisfies the common strong Pareto assumption, maximizing efficiency is a necessary condition for welfare maximization. We thus take the first step before the second and ask what an efficient climate policy would look like.¹

In addition, we assume that climate conditions exist that maximize economic output in any region. As climatic conditions differ across the globe, not all countries face the output-maximizing climate at the same time. In general, climate is understood as the (full) weather statistics in a large region (such as a significant section of a country) over a long period (such as 30 years). In this paper we consider a stylized static framework and represent the climate by country-specific climate conditions. At this point we present the approach in terms of temperature only, in the quantitative analysis we also include precipitation. We set up the model such that there is a unique output-maximizing temperature level, showing that the globally efficient level of SRM deployment minimizes an economic output-weighted average of the gap between current country-specific temperature and the output-maximizing level.

We assume that country i 's economic output, Y_i , at time t can be represented by

$$\ln Y_i(t) = \bar{F}_i(t) - \varphi(T_i(t) - T^*)^2 \quad (1)$$

where parameter φ represents the sensitivity of Y to local temperature and parameter T^* is the output-maximizing temperature, which we assume to be time-invariant. The term $\bar{F}_i(t)$ encompasses all other country-specific terms. We model local (country-specific) temperature at time t as

$$T_i(t) = \bar{T}_i + \sigma_i S(t) - \theta_i R(t), \quad (2)$$

where local temperature responds to non-SRM anthropogenic forcing, $S(t)$, and SRM, $R(t)$, in a country-specific way, as captured by the positively valued parameters σ_i and θ_i , respectively, and where \bar{T}_i encompasses all other country-specific temperature determinants. We impose the constraint $R(t) \geq 0$, i.e. we do not study the possibility of (solar) radiation management deployment to increase global temperatures, as counter-climate engineering measures are expected to face considerable practical obstacles (Parker et al., 2018; Heyen et al., 2019). In the following, we suppress the time argument (t) to simplify notation. The effect of SRM on the economic output of country i is now given by.

$$\frac{dY_i}{dR} = \theta_i Y_i 2\varphi(\bar{T}_i + \sigma_i S - \theta_i R - T^*). \quad (3)$$

The expression measures the marginal private benefits of global SRM. The incentives to engage in SRM depend positively, first, on effective market size $\theta_i Y_i$ and, second, on local temperature if it greatly exceeds optimal temperature (without the constraint $R \geq 0$, the second aspect would generalize to large incentives if local temperature differed widely from optimal temperature).

We assume that SRM deployment generates cost $C(R) = cR$, where $c > 0$ is the constant marginal cost of SRM. By summing expression (3) over countries i , equating the sum to marginal

cost c , and solving for R , we find that the level of SRM that maximizes the aggregate output of a group of countries I (all or a subset, i.e., coalition) is characterized by²

$$R^I(t) = \sum_{i \in I} \left(\frac{\theta_i Y_i(t)}{\sum_{j \in I} (\theta_j)^2 Y_j(t)} \right) (\sigma_i S(t) + \bar{T}_i - T^*) - \frac{c/2\varphi}{\sum_{j \in I} (\theta_j)^2 Y_j(t)} \quad (4)$$

The second term is the marginal cost of SRM corrected for the effect of SRM on aggregate output. Most action comes from the first term, representing marginal benefits. In the first term, the second factor is i 's deviation from optimal temperature in the absence of SRM, "temperature gap" for short. Obviously, if this gap were zero for all countries, there would be no incentive for SRM. If each country would consider its original temperature level as optimal, i.e. if $T^* = \bar{T}_i$ in (4), we would encounter the problem addressed by Moreno-Cruz et al. (2012) and Ricke et al. (2013) (and by assuming $c = 0$, as they neglect operational cost for SRM application). With perfect SRM (i.e., $\sigma_i = \theta_i$), the efficient level of SRM would simply offset greenhouse-gas forcing ($S = R$) in their problem.

Here, with an optimal temperature T^* and asymmetric countries, geographical heterogeneity (captured in \bar{T}_i) makes it impossible for SRM to optimize temperature everywhere simultaneously. In this case, the efficient level of SRM will respond to the weighted average of temperature gaps across the countries, where the relative weights (the terms in long brackets) are governed by the relative local sensitivity of temperature to SRM (θ_i) and relative output. When output variation is stronger than the variation in local temperature sensitivity to SRM, the temperature gaps of high-income locations will be the main drivers behind the efficient level of SRM.

Accordingly, eq. (4) reveals the effects on SRM of changes in the background climate conditions $S(t)$, the background economic conditions, $Y_i(t)$ or a change in the coalition I of countries that jointly decides on the level on the efficient SRM level. First, when S is higher (as climate change progresses), the efficient level of SRM is affected through the temperature gap. Due to a higher S , temperature is higher in all locations, which for given weights increases the demand for SRM: warm countries will prefer more cooling and cool countries less warming. Second, the weights shift under changing economic conditions. Convergence in economic growth would imply that currently rather poor (and mostly warm countries) will in economic terms gradually catch up with developed countries, their relative weight would increase in (4) and the globally efficient SRM level becomes higher (under the assumption that this effect dominates a possible increase in "optimal" temperature due to adaptation). The third point refers to the coalition case: we see that when a new country joins the coalition, efficient SRM moves in the direction that the joining country prefers since the coalition starts weighting the output contribution of the new member: more SRM if a warm country joins, as measured by the temperature gap $\bar{T}_i + \sigma_i S - T^*$, and less SRM if a cold country joins. We analyze these implications in more detail below.

2.2. Calibration

To account for the (regionally) uneven influence of SRM deployment on climate, we include not only the effect on temperature but also the effect on precipitation, both measured at the 1-degree latitude by 1-degree longitude grid-cell level. Both temperature and precipitation affect grid-cell economic output. The former is calibrated on the basis of Earth-system model simulations from Ricke et al. (2012) and the latter is calibrated on the basis of the G-Econ data (Nordhaus, 2006). The

¹ If international transfers are not freely possible, a welfare maximum might not maximize aggregate economic output. However, in that case the key question becomes what exactly are the limits to international transfers of economic resources and whether it is really optimal to use modifications of the climate system to compensate for non-existent opportunities for the transfer of economic resources. Such an analysis would focus on the institutional ties of international politics to an extent that goes beyond the scope of the present paper.

² The expression is not a closed-form solution since the RHS contains Y , which depends on R . Nevertheless, the expression allows for straightforward comparative statics since the Y -dependent weights add up to unity (after multiplying and dividing the expression inside the summation sign by θ_j).

G-Econ data provides information on Gross Cell Product (gross value added at the grid-cell level) and long-term average temperature and precipitation conditions (1975–2005). For the SRM decision, we consider climate and economic background conditions possibly prevailing in the middle of the century (year 2050) as projected by the baseline SSP scenarios (Riahi et al., 2017)

For our calibration, we assume that average grid-cell temperature and precipitation, T_j and P_j , respectively, affect gross grid-cell product GCP_j and are determined by the global level of SRM deployment and the (multidimensional) state of non-SRM anthropogenic forcing, R and S , respectively (both measured in W/m^2). The state of non-SRM anthropogenic forcing is determined by prevailing greenhouse-gas (GHG) forcing and tropospheric-aerosol forcing (saer). As the effect of SRM deployment on global and regional climate is very much faster than greenhouse-gas-driven climate change (Lenton and Vaughan, 2009; Klepper and Rickels, 2014), we consider S as exogenously given (represented by \bar{S}_t to reflect the different climate background conditions across the five baseline SSP scenarios in 2050, Riahi et al., 2017). Accordingly, the only decision variable for countries that allows a rapid change in temperature and precipitation is R , and country i 's economic output, measured by gross value added (GVA), is given by the sum of the grid-cell products (GCP) either fully or partly located in country i , $j \in J^i$,

$$GVA(R, \bar{S}_t, Z_{it}) = \sum_{j \in J^i} GCP(T_j(R, \bar{S}_t), P_j(R, \bar{S}_t), X_j, A_j, Z_{it}) \quad (5)$$

Here we include argument t to take into account different background conditions. X_j summarizes parameters describing cell-fixed geographic control variables, A_j specifies the area size of grid cell j in country i , and Z_j specifies country-fixed effects for country i , the latter also capturing the SSP-specific growth projections for economic output.

Globally, the optimal level of SRM maximizes aggregate economic output of all N grid cells, net of the cost of SRM:

$$\max_R \sum_{j=1}^N GCP(T_j(R, \bar{S}_t), P_j(R, \bar{S}_t), X_j, A_j, Z_{jt}) - C(R) \quad \text{s.t. } R \geq 0, \quad (6)$$

$$Z_{jt} = Z_{it} \quad \text{for all cells } j \text{ in country } i$$

with the first-order condition for a globally efficient solution:

$$\sum_{j=1}^N \left(\frac{\partial GCP}{\partial T_j} \frac{\partial T_j}{\partial R} + \frac{\partial GCP}{\partial P_j} \frac{\partial P_j}{\partial R} \right) - c = 0 \quad (7)$$

We estimate changes in GCP as a function of grid-cell temperature and precipitation with a cross-section estimation following Nordhaus (2006), also including other geographic control variables like distance to coast or elevation (Appendix B). The 1-degree latitude by 1-degree longitude grid cells are assigned to countries proportionally to the area of the country in the grid cell, yielding a total number of 16,082 GCP observations.

We use a linear quadratic specification for the global influence of temperature and precipitation to explain GVA-weighted variation in the logarithm of GCP . In contrast, Nordhaus (2006) bases his forecast of the economic impact of climate change on country-specific impacts of temperature change and a unique global impact of the influence of precipitation changes.³ While such an approach is suitable for predicting the impact of a given climate-change scenario, it is not suitable for optimizing the impact of the climate (via SRM) because the

³ In his approach to explaining the influence of climate on economic output, he takes into account higher moments of the climate statistics (e.g., maximum of temperature). This is reasonable because the impact of regional climate on economic output is probably not restricted to the mean values for temperature and precipitation. But there is rarely any comprehensive forecast available on how higher features respond to climate change, not to mention SRM at the grid-cell level. However, restricting the forecast of impacts to mean temperature and precipitation changes is meaningful because moments of climate statistics tend to scale with the mean changes (e.g. Osborn et al., 2018).

coefficients of Nordhaus's specification imply implausible results for several specific cases, including for example optimal temperatures for the US of 80.05 °C, Canada of 141.86 °C, Botswana –406.18 °C, and Egypt –229.12 °C. For that reason, we have restricted our specification to the global influence of temperature and precipitation on economic output. Given the high leverage of SRM and the possibility of overcooling, we believe that a global specification is a meaningful way of capturing the possible range of the temperature and precipitation response to SRM deployment. The specification provides unique optima for temperature and precipitation.

We have estimated $T_j(R, S)$ and $P_j(R, S)$ as linear functions of SRM and the state of the climate by using the HadCM3L general-circulation model as set out in Ricke et al. (2012) (Appendix A). We have thus obtained estimates for 20,577 grid cells (of which 16,082 are matched with the information on GCP in the corresponding cells). For all grid cells, the deployment of SRM reduces grid-cell temperature, $\partial T_j / \partial R < 0$, albeit to different magnitudes. In 14,646 grid cells, SRM reduces precipitation ($\partial P_j / \partial R < 0$), but in the remaining grid cell it increases precipitation ($\partial P_j / \partial R > 0$). The influence of future GHG and SRM forcing on grid-cell temperature and precipitation is uncertain. Both the magnitudes and the patterns of the projected changes vary greatly (Collins et al., 2013): (i) by scenario and (ii) by model (the GCM selected here for illustration – HadCM3 – is a model with middling climate sensitivity in terms of the range simulated by various models). Still, the estimates for grid-cell change in temperature and precipitation applied here provide a reasonable representation of regional variation in the effectiveness of SRM in compensating for GHG-induced changes (Ricke et al., 2012).

The estimation suggests a GVA-maximizing temperature increase of 1.49 °C [0.47 °C] above the average temperature between 1975 and 2005 (i.e. the linear influence of temperature and precipitation is positive and the quadratic influence is negative).⁴ It should be noted that the estimates on optimal temperature increase estimates are not directly comparable to estimates from integrated assessment models because the latter usually use global mean temperature (increase) as an indicator with full spatial coverage including temperature increase over the oceans, whereas our temperature data covers only a subset, i.e. the terrestrial grid cells.⁵ Still, the estimated GVA-maximizing temperature is in the same ballpark as the IAM-meta-analysis-based estimate by Tol (2016), who derives an average optimal temperature increase of 1.7 °C (with a standard deviation of 1.5 °C) if countries are weighted by their 2005 GDP levels.⁶ The specification is robust against different representation of cell area size (which is decreasing with latitude). Using instead GVA density (i.e. $\ln(GVA/area)$) as dependent variable also suggests an optimal temperature increase of 1.49 °C [1.00 °C]. Using latitude as further explanatory variable is prevented by multicollinearity issues and instability in the coefficients of interest (i.e. with respect to temperature and precipitation). We include a dummy variable to account for cells close to and above the polar circle. Dropping this dummy variable would instead imply an optimal temperature increase of 1.59 °C [0.45°]. Table B.T1 in Appendix B provides details on the different specifications.

The estimation suggests a GVA-maximizing precipitation increase of 979 $mm/m^2/year$ [58.42] above the average precipitation between 1975 and 2005. While some IAM-based analyses explicitly take the influence of precipitation into account (e.g., Tol, 2002, Aaheim et al., 2012), we are

⁴ The standard errors have been approximated by the propagation of error from the standard errors of the linear and quadratic term in the estimation, i.e. $T_{opt} = \partial \ln GVA / \partial T = \beta_1 - 2\beta_2 = 0$ and $\sigma_{T_{opt}/T_{opt}} = \sqrt{(\sigma_{\beta_1}/\beta_1)^2 + (\sigma_{\beta_2}/\beta_2)^2}$.

⁵ An increase of global mean temperature by 1.5 °C implies substantially higher warming over land. For example, Seneviratne et al. (2018) show from Earth System Model simulations increases of 2 °C and 2.3 °C respectively over continental USA and central Brazil.

⁶ Using GVA measured in PPP instead of market exchange rates (both for 2005) suggests an GVA-maximizing temperature increase of 1.53 °C [0.91 °C, 2.16 °C].

not aware of any studies providing information with respect to optimal precipitation. Compared with the status quo, our estimated increase is in the vicinity of current mean global precipitation, pointing up the limitations of our specification and indicating that our optimal value is probably too high.⁷ But reduced precipitation (or changed precipitation patterns) are considered a critical impact limiting or even preventing the deployment of SRM (e.g. Robock et al., 2008). An alternative would have been to include a lower limit on precipitation as a constraint. Roshan et al. (2019) show that under such regional constraints on precipitation (derived to correspond with the Paris temperature targets) SRM deployment is greatly reduced in comparison with a temperature-constraint-only framework. However, there is no globally agreed lower level for annual precipitation, and we are more interested in the trade-off between moving temperature closer to its optimum at the cost of moving further away from the precipitation optimum. Note that the latter has a much smaller curvature than the former.⁸

For our calculations of gains or potential payments as part of the global SRM decision, we require information about GVA in levels, not in logarithms. When making the transformation we need to take into account that the exponent of the expectation is not the expectation of the exponent. If error terms are normally distributed, retransforming a log-linear model of the form $\ln(y) = \beta x + \varepsilon$ would be achieved via $E[y|x] = \exp(\beta x) \exp(0.5\sigma_\varepsilon^2)$ (e.g., Manning and Mullahy, 2001). Alternatively, if the assumption of non-normal distributed error terms is violated, Duan's smearing retransformation can be used, $E[y|x] = \exp(\beta x) \frac{1}{N} \sum_i^N \exp(\varepsilon_i)$ (Duan, 1983). However, to provide unbiased estimates, the smearing retransformation requires homoscedastic error terms. Following Nordhaus (2006) in estimating the impacts of (avoided) climate change, we have chosen a weighting strategy enabling us to maximize accuracy and not to minimize heteroscedasticity (which would have required a different weighting scheme). Accordingly, in focusing on predicting the impacts of changes in temperature and precipitation to calibrate our model, our aim was to minimize the standard error of estimation calculated not at the grid-cell but at the country level. Lütkepohl and Xu (2012) show that although in theory an optimal predictor (i.e. with correction) will minimize forecast standard error, the absence of proper estimation of forecast error variance implies that the optimal predictor does not have necessarily an advantage over the naïve predictor (i.e. without correction). With our calibration, the SE of the estimate at the country level is 510.781 with country-specific smearing corrections and 283.972 without them. Accordingly, we focus on the naïve forecast.

With our relatively large observation units (spatial resolution 1 degree latitude by 1 degree longitude) we assume that spatial spillovers occur only within grid cells and not across them. Knowledge spillovers are a prominent example for creating spatial autocorrelations in empirical investigation. They are however usually assumed to take place in rather small spatial resolutions. Furthermore, without a sound economic description of spatial interdependence, we would need to derive the spatial weighting matrix by data-analytic approaches or by guesswork. However, differently specified weighting matrixes would produce very different estimates of spatial spillovers in our data, resulting in very weak identification (Harris et al., 2011 and Gibbson and Overmann, 2012, respectively). Even worse, a relatively arbitrary weighting matrix may incorrectly identify the existence of a spillover mechanism (Corrado and Fingleton, 2012), blurring the causal

economic processes at work by indicating "pointless" spatial econometric relationships (Gibbson and Overmann, 2012). Accordingly, given that our aim is to calibrate our model against an inverted U-shaped relationship between climate (measured by temperature and precipitation) and economic output, we expect no advantages from including a data-driven derived spatial weighting matrix.

However, restricting the calibration of the influence of temperature and precipitation on grid-cell GVA by a cross-sectional relationship has several intrinsic limitations. In particular, the relationship may capture historical processes that would not be effective in future conditions of climate change (or at least not in those timescales) (Dell et al., 2014). However, the grid-cell-based approach is essential to take into account the regionally imperfect compensation of greenhouse-gas-induced changes in temperature and precipitation induced by SRM deployment (Moreno-Cruz et al., 2012; Ricke et al., 2013).

To take into account the changing gap between, and relative weighting of, country-specific and output-maximizing climate levels over time resulting from climate change and economic growth respectively, we draw upon the SSPs' baseline projections for the middle of the century (year 2050). The baseline scenarios project future developments stemming from the current (climate) policy framework, while leaving new climate policies (like net-zero emission targets) out of the equation. To take account of economic growth, we obtained two growth projections for each SSP from the baseline scenario, thus representing two different growth models. For the SSPs, the IIASA database includes three different baseline growth models of which two—the one provided by the OECD (Dellink et al., 2017) and the IIASA (Cuaresma, 2017)—have country projections making it possible to extrapolate the economic output of countries included in the GEcon database. While the IIASA growth model places greater weight on growth induced by human capital increase, the OECD growth model places larger relative weight on the long-term growth rate of total factor productivity. In multiplying the country GCPs with the country growth rates, we assume that GVA in each grid cell of a country grows at the same rate.

The OECD and IIASA growth model specifications reflect different degrees of growth convergence for the different SSPs. Growth convergence implies that poorer countries are catching up with richer countries, which means per capita incomes across countries are getting closer to each other (for a recent review and empirical analysis on this topic, see Johnson and Papageorgiou, 2020). All ten baseline growth SSPs scenarios have a significant negative correlation (at the 1% level) between per capita GDP (in 2005 USD at market exchange) and growth (until 2050), both implying that poor countries are projected to have a stronger growth than rich countries (correlation ranging between -0.48 and -0.23 for OECD SSP3 and IIASA SSP4, respectively). Accordingly, σ (measured by the standard deviation of log per capita GDP in USD 2005 at market exchange rates) drops from 1.67 and 1.73 for the OECD and IIASA baseline in 2005, respectively, to between 1.54 and 1.04 (OECD; SSP4 and SSP5) and to between 1.66 and 1.27 (IIASA: SSP3 and SSP5).⁹ At the same time, per capita GDP (in 2005) has a significant negative correlation (-0.49) with country long-term mean temperature (obtained as the simple mean of grid-cell temperature assigned to a country). These figures are important in the light of our formula for optimal SRM deployment, eq. (4): they suggest that on average the relative weight assigned to the temperature gap of currently poorer but warmer countries increases and that the temperature gap itself of these countries also increases, while the temperature gap of colder countries decreases due to climate change. To take climate change into account, we obtained the SSP-specific projections for the increase in Kyoto Gases and Aerosol Forcing (as derived in each SSPs baseline-marker scenario).

Estimates for the marginal operational cost of global SRM, $c(R)$, were obtained from a recent study by Moriyama et al. (2017). They review

⁷ We tested alternative specifications describing the influence of precipitation by higher-order polynomial functions or in a linear-quadratic specification based on the log of precipitation. The former resulted in odd results during optimization (to the presence of more extrema), the latter in an even higher optimal precipitation level than the one obtained here.

⁸ The degree of curvature, i.e. $|k(x)| = f''(x) / (1 + f'(x)^2)^{3/2}$, is 0.0168045 and $5.82 \cdot 10^{-7}$ respectively for temperature and precipitation at their optimum. A value of 0 implies a straight line.

⁹ Note that IIASA and OECD scenarios differ in their baseline value for sigma convergence because of slightly different country coverage in the projections.

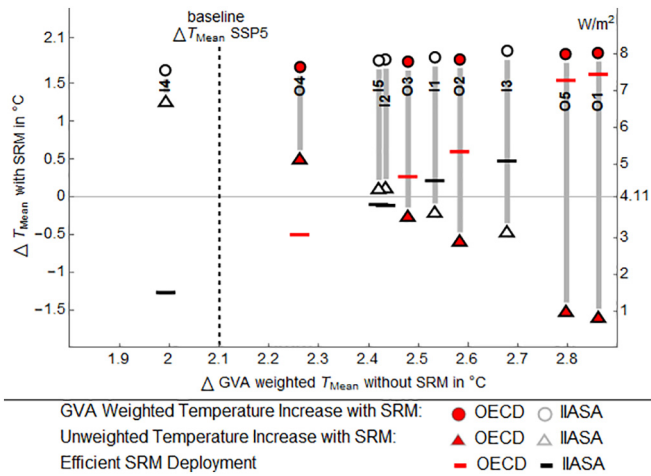


Fig. 1. Efficient SRM deployment and temperature. The figure shows the GVA-weighted temperature increase without SRM deployment (x-axis) resulting from the different growth projections across the SSPs scenarios, the corresponding efficient levels of SRM deployment (right y-axis), and the resulting weighted and unweighted temperature increases under these SRM deployment levels (left y-axis). The climate-background conditions for all scenarios are given by the SSP5 baseline scenario, resulting for our calibration in an unweighted temperature increase of 2.1 $^{\circ}\text{C}$.

and estimate the cost for stratospheric aerosol injection (SAI), which is probably the most likely technology to be considered in the case of global SRM deployment. Furthermore, the most likely injection method is expected to be achieved by aircraft, and Moriyama et al. (2017) estimate the cost to be USD 45 bn (USD/yr)/(W/m²) or USD 5 bn (USD/yr)/(W/m²), using either existing aircraft (F-15) or newly designed aircraft respectively. If not indicated otherwise, the efficient level of SRM deployment is derived for the operational cost estimate of USD 45 billion/year/W/m².

3. Results

3.1. Globally efficient SRM deployment

We calculate the efficient level of SRM deployment across all possible combinations of economic background and climate conditions, resulting in 50 scenarios. Across all scenarios, the average level of SRM deployment is 3.72 [1.78] W/m² in 2050.¹⁰ Our calculation shows that the variation in the efficient level of SRM is considerably larger across the 10 different economic-growth scenarios than the variation across the 5 different climate-change scenarios (average standard deviation is 1.7 W/m² versus 0.5 W/m², respectively; see Table C.T1 and C.T2 in Appendix C). In all but SSP3, the OECD growth projections result in a higher level of SRM deployment than the IIASA growth projections despite the same climate background conditions, indicating that the effect of economic growth and convergence is more pronounced in the OECD growth projections. Within growth projections, the largest difference is observed between SSP5 and SSP4 for the OECD growth projections (7.27 versus 2.12 W/m², respectively) and between SSP3 and SSP4 for the IIASA growth projections (4.03 versus 0.57 W/m²).¹¹ The difference in the efficient level of SRM is larger than the difference in climate

¹⁰ Using instead the alternative specification with $\ln(\text{GVA}/\text{area})$ as dependent variable implies an average optimal SRM level of 3.91 [1.77]. Dropping the influence of high latitudes in the specification which resulted in an optimal temperature increase of 1.59 compared to 1.49 implies that the average optimal SRM level reduces to 3.27 W/m².

¹¹ Without accounting for high latitudes by a dummy variable results for $\ln(\text{gva})$ as dependent variable in 3 out of 50 scenarios and for $\ln(\text{gva}/\text{area})$ as dependent variable in 2 out of 50 scenarios in zero optimal SRM (i.e. a constraint solution). For both this applies for the case of IIASA growth projections under SSP4 for climate background conditions as given by SSP1, SSP2, and SSP3 and climate background conditions SSP1 and SSP2, respectively. See Tables C.T4 to C.T6 in Appendix C.

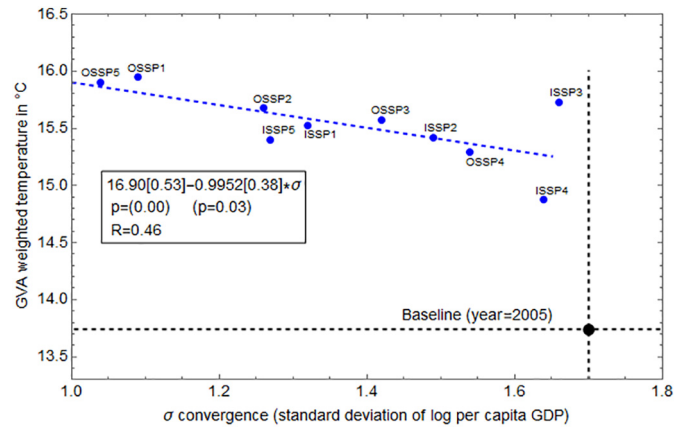


Fig. 2. GVA-weighted temperature in different economic growth scenarios. The figure displays global mean GVA-weighted temperature using the growth projections from the OECD (O) and the IIASA (I) for the 5 SSP baseline projections until (2050). Neither climate change (increasing temperature) nor climate impacts (decreasing the weights of affected countries) are included in the calculated mean temperatures.

background conditions, the total forcing in SSP3, SSP4, and SSP5 is 4.29 W/m², 4.29 W/m², and 4.837 W/m² respectively.

Fig. 1 summarizes the main results for the 10 different economic-growth scenarios under a climate-change scenario given by SSP5. It first displays the efficient SRM level dependent on GVA-weighted temperature increase without SRM deployment (dashes), and second, the resulting weighted and unweighted temperature increase under SRM deployment (circles and triangles respectively; see also Table C.T3 in Appendix C). The climate background conditions are as projected in the SSP5 baseline-marker scenario in 2050, resulting in an unweighted temperature increase of 2.1 $^{\circ}\text{C}$ against the average over the period 1975 to 2005. Because of different assumptions on economic growth across the SSPs and the growth models, the weighted temperature increase without SRM varies between 1.99 $^{\circ}\text{C}$ and 2.86 $^{\circ}\text{C}$ for IIASA-based growth projections in SSP4 and OECD-based growth projections in SSP1 respectively.

We observe the following patterns: Connecting the dashes, we find an upward-sloping line. The globally efficient level of SRM is monotonically increasing with the GVA-weighted global mean temperature, implying that this is a meaningful indicator for the given purpose. It highlights the first-order reason-driver behind SRM: “cool if the globe warms up.” Connecting the circles indicates a flat relationship, showing the optimal GVA-weighted mean temperature. Connecting the triangles, we find a descending line. As the countries in warm regions with a preference for cooler temperatures gain economic importance (so the GVA-weighted global mean temperature goes up), the efficient level of SRM increases and hence the meteorological mean global temperature decreases. Fig. 1 shows that in 6 out of 10 scenarios (SSP1 and SSP3 with IIASA growth assumptions and all SSPs except SSP4 with IIASA growth assumptions) efficient SRM deployment implies overcooling in the sense that the unweighted mean temperature is reduced below its baseline value (average over the period from 1975 to 2005).¹²

This is partly explained by the underlying assumption of growth convergence in the SSPs: under most SSPs, relatively poor and already warm countries are catching up with developed countries in terms of economic growth. Accordingly, these countries gain relatively more weight in the determination of the efficient level of SRM deployment, implying that a stronger decrease in unweighted temperature is required to achieve the same decrease in weighted temperature. Fig. 2

¹² Irrespective of the specification (i.e. either $\ln(\text{GVA})$ or $\ln(\text{GVA}/\text{area})$ as dependent variable, with and without controlling for high latitude, 6 out of 10 scenarios under climate background conditions as given in SSP5 result in an overcooling.

shows GVA-weighted mean temperature under the 10 different economic growth scenarios (without climate change and without SRM deployment). The figure shows that on average growth convergence explains a significant fraction of the increase in GVA-weighted mean temperature, but also that growth convergence is not a necessary precondition for increases in GVA-weighted temperature resulting from changing relative weights as can be seen from the efficient level of SRM under the growth projections of IIASA SSP3.

We find that for our model framework the appropriate indicator capturing the different effects is GVA-weighted mean global temperature increase. In this indicator, climate change affects regional temperatures, while climate impact and economic growth affect the GVA weights.

Fig. 3 shows the decomposition of the GVA-weighted temperature increase for climate and economic background conditions as given by SSP5 under the IIASA growth assumptions in 2050 (without SRM). The weighted temperature increase is effected by i) the actual temperature increase due to *climate change* (lower left corner), ii) the changes in weights due to *economic growth* (top corner), and iii) the changes in weights due to the *impact* of temperature on economic output (lower right corner). The corner values show the temperature increase for the effects in isolation, the values on the legs show the temperature increase of two effects combined, and the value in the middle shows the overall weighted temperature increase. The figure indicates that even without climate change (i.e. using the baseline temperature values) the weighted temperature rises by 1.7 °C alone due to increasing relative weights of warmer (developing) countries over and against cold (developed) countries. Combined with climate change, this would result in an increase by 3.71 °C (left leg). However, climate change has an impact on economic output, affecting warmer regions more than proportionally and implying decreasing relative weights for warmer (developing) countries compared to cold (developed) countries. However, the reduction in weights due to climate-change impacts is dominated in both dimensions, implying that the increase in temperature is larger than the reduction in weights (lower leg) and that the increase in weights due to economic growth is larger than the reduction in weights due to climate change (right leg).

With SRM deployment, the GVA-weighted temperature increase reduces to on average 1.82 °C compared to an average weighted temperature increase of 2.53 °C without SRM (under the climate-background conditions given by SSP5 in 2050, see Fig. 1). This is still larger than the suggested optimal temperature following from the quadratic linear temperature specification (1.49 °C). Furthermore, the weighted temperature increase with SRM deployment varies between 1.62 °C and 1.92 °C across the scenarios. Note that we optimize GVA not against

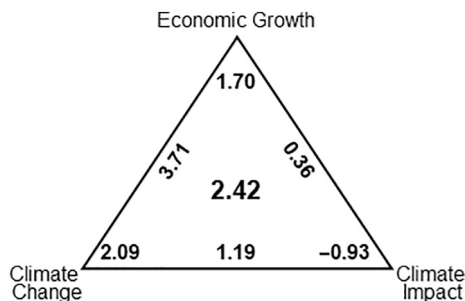


Fig. 3. Decomposition of weighted temperature increase. The figure shows the increase in GVA-weighted temperature broken down into isolated effects: climate change (change in weighted temperature due to forcing at fixed GVA weights), economic growth (change in weighted temperature due to change in GVA weights arising from growth only), and climate impacts (change in weighted temperature due to change in GVA weights arising from effect of temperature on GVA only), displayed in the lower left, top, and lower right corners respectively. The GVA-weighted temperature increase for two effects combined is displayed on the legs and the overall GVA-weighted temperature increase in the center.

Table 1
Gains from SRM deployment in percent of GVA.

Operational cost	Growth assumption	SSP1	SSP2	SSP3	SSP4	SSP5
45bn USD W/m ²	OECD	2.10	1.06	0.88	0.41	3.01
	IIASA	0.74	0.54	1.17	0.07	1.16
5bn USD W/m ²	OECD	2.30	1.22	1.07	0.49	3.20
	IIASA	0.86	0.64	1.39	0.10	1.28

temperature but against SRM deployment, thus also taking into account the influence of SRM on precipitation and the regionally uneven compensation of SRM for greenhouse gas-induced temperature and precipitation changes. If we assumed that SRM only affected temperature but not precipitation, average SRM deployment across all scenarios (i.e. all combinations of economic and climate background conditions in 2050 given by the SSPs) would increase by 2.04 W/m². For climate conditions as given by SSP5, the efficient SRM level would then reduce the weighted temperature increase to on average of 1.53 °C (max 1.61 °C and min 1.43 °C). If we assumed in addition that SRM induced no operational cost, the average SRM deployment across all scenarios (i.e. all combinations of economic and climate-background conditions) would increase by a further 0.44 W/m². For climate conditions as given by SSP5, the efficient SRM level without impact on precipitation and without operational cost would then reduce the weighted temperature increase to an average of 1.48 °C (max 1.54 °C and min 1.37 °C).

Despite the fairly strong impacts on weighted and in particular on unweighted temperature increase, the gains in global GVA from SRM deployment are modest. Table 1 shows the percentage gain in GVA from SRM deployment relative to the situation without SRM deployment for the two different cost assumptions. The figures show that at the margin the operational cost has a small but noticeable influence on the efficient SRM level. The rather modest impacts overall indicate the gains accruing to climate-change losers (and SRM winners) net of the losses incurred by climate-change winners (and SRM losers). Accordingly, we now adopt the country-specific perspective.

3.2. Individual country incentives for SRM deployment

The heterogeneous economic interests involved in SRM deployment under future climate conditions are more nuanced than the mere distinction between climate-change losers and winners. Fig. 4 shows the country-specific incentives to undertake SRM for climate and economic background conditions as projected in SSP5 under IIASA growth projections in 2050. The axes show the marginal change in GVA as a function of SRM: the x-axis at the point of no SRM deployment and the y-axes at the point of globally efficient SRM deployment (as derived in Table C.2 in Appendix C). Accordingly, the x-axes address the question whether country *i* has an economic interest in embarking on SRM deployment at all, and the y-axes address the question whether country *i* has an economic interest in stepping up SRM deployment beyond the globally efficient level. The size of the bubble shows the absolute change in GVA between the situation of no SRM and globally efficient SRM deployment, the color code indicates whether GVA increases (orange) or decreases (purple). In addition, Fig. 4 shows on both axes the marginal cost for SRM deployment corresponding to injecting aerosols into the stratosphere using existing airplanes (USD 45 billion/year/W/m²). As we are talking about a deployment of SRM in the year 2050, one might expect newly designed aircraft to be used for the spreading of aerosols, thus reducing marginal cost. However, the cost estimates presented in Moriyama et al. (2017) and similar assessments usually assume global coordinated deployment, which implies relatively low marginal costs, for example for the best-located airports to be used. Turning to the question of individual countries' incentives for potentially unilateral SRM deployment, the assumptions underlying the cost estimates with

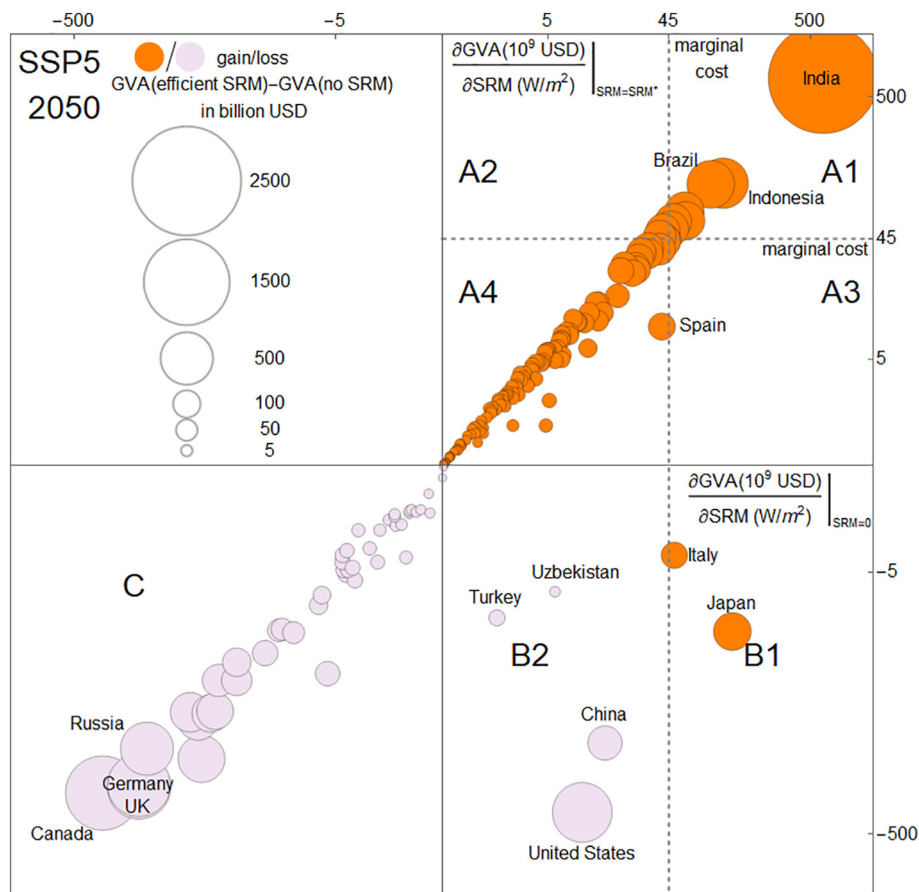


Fig. 4. Individual country interests in SRM deployment in 2050 for SSP5. The figure shows the marginal change in Gross Value Added (GVA) with no SRM ($SMR = 0$, x-axes) and with globally efficient SRM deployment ($SRM = SRM^*$, y-axes) for climate and economic-background conditions as given in SSP5 under the IIASA growth projections for the year 2050. The size of the bubble shows the absolute change in GVA and the color code shows whether a country gains (orange) or loses (purple) from SRM deployment.

respect to processing, infrastructure, or monitoring are likely to be on the optimistic side, therefore we feel that the marginal cost displayed is probably rather a low estimate for the operational cost incurred in the case of unilateral deployment.

Climate-change losers are expected to gain from SRM deployment and are situated in the positive domain of the x-axes. However, not all of them could afford SRM deployment unilaterally and not all of them would gain from SRM deployment at the globally efficient level. For that reason, we distinguish theoretically between six groups of countries in the positive domain of the x-axes, 4 groups in the positive domain of the y-axes (A1, A2, A3, and A4), and two groups in the negative domain of the y-axes (B1 and B2).

There is only a small group of A1 countries (7 countries in the SSP5 scenario with IIASA growth projections) where the marginal gain in GVA exceeds the marginal cost of SRM at both points (*no SRM* and *globally efficient SRM*). These countries would have an incentive to deploy SRM unilaterally because they would gain by increasing SRM application beyond the globally efficient level. The majority of climate-change loser countries (and countries in general) would rather free-ride (A4 with 118 countries in the SSP5 scenario). These countries also gain at both points of SRM deployment, but their marginal gains fall short of the marginal costs of SRM deployment. According to these results, the “Tuvalu Syndrome” cannot be considered a credible threat. This syndrome means that for small (and in particular island) states the best response would be to commit themselves to unilateral SRM deployment to such that the best response of other countries is to collectively reduce emissions (Millard-Ball, 2012; Moreno-Cruz, 2015).

There are two more groups of countries with positive marginal gains at both levels of SRM deployment. For the countries in area A2 (two countries), the gains exceed the marginal cost of SRM deployment only at the *globally efficient SRM* level. The explanation of this is the non-concavity of our functional form for the grid-cell influence of temperature and precipitation on GVA (in levels). The interpretation is that these countries would benefit sufficiently from the implementation of the efficient level so that their marginal SRM benefit would even exceed the marginal cost of SRM deployment. Countries in area A3 would have an incentive for unilateral SRM deployment in the case where *no SRM* is realized. However, if *globally efficient SRM* is already in place, their incentives to further increase SRM deployment is not sufficient due to the marginal cost. There are no countries in A3 for any SSP scenario under the IIASA growth projections, but one country (Japan) for SSP4 and SSP5 under the OECD growth projections.

The countries in the B area can still be considered climate-change losers as they would gain from SRM deployment. But from their perspective, deploying SRM at the *globally efficient* level is already overdoing it. The countries in the B1 area (two countries) still gain from SRM deployment in absolute terms. This is not true of countries in the B2 area (six countries). Even though these countries are (moderate) climate-change losers and would benefit from reducing global temperatures, the *globally efficient SRM* level implies that in absolute terms they would lose from SRM deployment. The remaining countries in area C are the climate-change winners (44 countries) from SRM deployment to whatever degree (if we allowed for counter climate engineering, i.e. $R < 0$, we would also need to distinguish between different groups

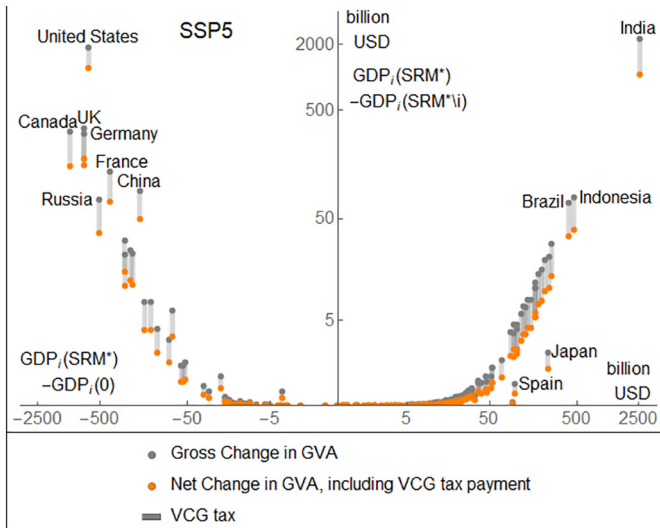


Fig. 5. Participation gains in SSP5 under IIASA growth assumptions. The grey dots in the figure indicate the country-specific absolute change in GVA between globally efficient SRM (full participation) and no SRM (x-axes) and between globally efficient SRM (full participation) and efficient SRM excluding country i (y-axes). The changes are derived under the climate- and economic-background conditions in SSP5 under the IIASA growth projections for the year 2050. In addition, the figure shows the cost for the remaining $N-1$ countries if country i is included, which is equal to the Vickrey-Clarke-Groves (VCG) tax. The orange dots indicate the net change in GVA caused by payment of the VCG tax.

among the C countries). Information about the distribution of countries for all SSPs under the two growth projections across the different incentive areas can be found in Table D.1 in Appendix D.

3.3. Participation gains in a global SRM agreement

Even climate-change winners have strong incentives to join a global agreement preventing exaggerated deployment of SRM. Fig. 5 shows the country-specific gains from participating in a global agreement on SRM for climate and economic background conditions as projected in SSP5 under IIASA growth assumptions for the year 2050. The x-axis shows the absolute change in GVA between *globally efficient SRM* deployment and *no SRM* deployment. The information is the same as with the bubble sizes in Fig. 4. The y-axis shows the absolute change in GVA between *globally efficient SRM* deployment and *efficient SRM* deployment for the remaining $N - 1$ countries if the effect of SRM on country i 's GVA is ignored. If country i 's interests are not considered, the resulting efficient level of SRM deployment is even further away from what country i considers optimal. In general, the effect scales with the strength of the country-specific interests. For example, if Canada stays outside the global agreement, the remaining countries would decide on a higher level of SRM than when Canada is included. Although Canada already loses if the globally efficient SRM level is deployed, it would lose even more if the effect of SRM on its GVA were ignored. If India stayed outside the global agreement, the remaining countries would decide on a lower level of SRM compared to full participation, implying that India would gain less compared to the situation where their desire for cooling the planet were taken into account. Countries located close to the origin in Fig. 4 have only small participation gains as their marginal gain or loss from SRM deployment is too small to change the optimal global level significantly. Accordingly, they have low (but strictly positive) values on the y-axis in Fig. 5.

Including country i and implementing the efficient level of SRM under full participation, R^* , instead of the efficient level of SRM for the $N-1$ countries, R^*_{-i} , comes at a cost: $\sum_{k \neq i} GDP_k(R^*_{-i}) - \sum_{k \neq i} GDP_k(R^*) + C(R^*) - C(R^*_{-i}) \geq 0$, which is strictly positive if $R^* \neq R^*_{-i}$. The vertical grey bars in Fig. 5 display the costs

resulting from including country i 's preferences in the decision about the global level of SRM deployment for the remaining $N - 1$ countries. The costs correspond to the payments under a Vickrey-Clarke-Groves (VCG) mechanism (Vickrey, 1961; Clarke, 1971; Groves and Loeb, 1975). Here our calculation of the lump-sum charge component is based on the Vickrey specification, which, in contrast to the Clarke specification, includes the full change in the operational cost (which increases or reduces the charge in the case of $R^* > R^*_{-i}$ and $R^* < R^*_{-i}$, respectively) (Loeb, 1977). A VCG mechanism prompts truthful revelation of a country's preferences in dominant strategies (Green and Laffont, 1977), which is important when taking into account uncertainty about the (possibly country-specific) optimal climate, implying that the optimal level of SRM can be considered private information of the respective country. The orange dots at the lower end of each bar indicate the net gains of country i , which are realized by participating in the global agreement if they have to pay the cost they induce for the $N - 1$ countries. Country i 's gross gains exceed the costs (induced for the $N - 1$ countries) if $R^* \neq R^*_{-i}$, implying that the incentives for joining the global agreement still exist (if $R^* = R^*_{-i}$, the gains and costs would be zero). If countries decide on the global level of SRM deployment under a VCG mechanism, climate-change winners (countries in the negative domain of the x-axes) would actually have an incentive to collude, submitting demands such that $R^* = R^*_i = R^*_j = 0$ (e.g., country i and j collude and neither of them are pivotal). Note that collusion would be harder to coordinate if counter climate engineering (i.e., $R < 0$) were possible.

Green and Laffont (1977) show that a Groves mechanism with dominant strategies cannot achieve budget balance, implying that even though the mechanism ensures the provision of an efficient level of the public good (i.e. SRM), it is not pareto-optimal. To deal with the budget-balance problem one can apply the Bailey (1997) redistribution rule, which distributes a share of the hypothetical Vickrey or Clarke tax surplus that would be obtained if country i were to abstain. Accordingly, the truth-telling incentives for country i are not affected. However, the redistribution rule merely mitigates the budget-balance problem and only achieves budget balance by chance (Tideman and Plassmann, 2017).

It should be noted that the changes in GVA displayed in Fig. 4 and Fig. 5 can be quite large for some countries. These results, however, are easy to reconcile as countries will have experienced substantial growth in GVA (in nominal terms) by the year 2050. Still, India for example is estimated to gain about 25% in GVA in the year 2050 if the globally efficient level of SRM is implemented as opposed to *no SRM* deployment. Clearly, these instantaneous changes in GVA levels appear unlikely and can be explained by the limitations of the cross-section approach, which potentially overestimates the magnitude of climate impact on economic output. Also, they indicate the limitations of the static decision framework, again assuming the immediate implementation of the *globally efficient* level of SRM. The associated rapid change in temperature and precipitation would cause (economic) cost, suggesting that a *globally efficient* SRM level would in fact be best approached by a smooth and gradually increasing deployment scenario (Keith and MacMartin, 2015).

3.4. Implications for coalition formation

Outside an international agreement, the group of countries A and in particular $A1$ (see Fig. 4) have a strong incentive to exaggerate the use of SRM. However, their gains would not be sufficient to compensate the remaining countries. Fig. 6 shows the GVA gains and losses of country groups with increasing coalition sizes for climate and economic-background conditions as projected in SSP5 under IIASA growth assumptions in the year 2050. We have not modeled the coalition-formation process, but simply assume that the form of the SRM coalition corresponds to the country groups identified in Fig. 4 (ranging from $A1$ to C), in the order of their economic interest in cooling the planet. Consequently, the first coalition we consider contains only $A1$ countries, the second coalition also contains $A2$ countries ($A1-A2$), the third coalition

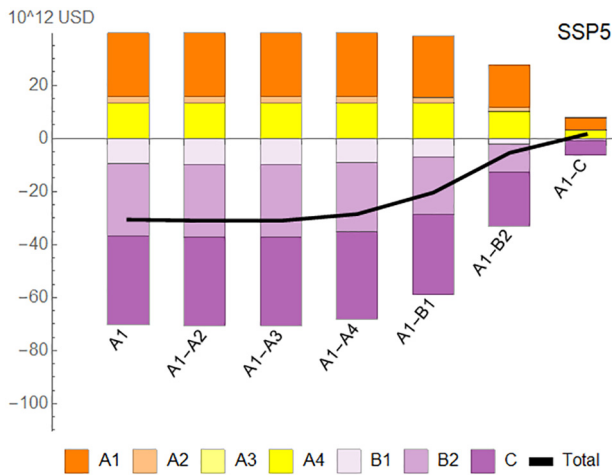


Fig. 6. Coalition gains and losses in 2050 and 2060. The figure displays, for coalitions of increasing size, the GVA gains and losses for the different country groups if the coalition determines the global level of SRM deployment by taking only the preferences of coalition members into account. The black line indicates the aggregated change in GVA of all countries. The changes are derived under climate and economic-background conditions as given in SSP5 under the IIA5A growth projections for the year 2050.

also A3 countries (A1-A3) and so on until we end up with the grand coalition (A1-C). In each case, the level of SRM deployment is assumed to maximize the aggregate GVA of the coalition members.

Fig. 6 emphasizes the incentives of A1 countries to free-ride. Their gains from exclusivity are large because they can choose a much higher level of SRM deployment on their own. However, while the rest of the A countries (in particular the A4 countries) benefit from free-riding on SRM deployment, from the perspective of the rest of the world SRM is exaggerated. In aggregated terms, the second effect dominates (SRM is exaggerated) and global change in GVA is negative. This situation remains similar for coalitions of increasing size up to the grand coalition in 2050. Even though participation of the B1 and B2 countries results in a significant reduction of the SRM level chosen by the coalition, the weight of the B1 and B2 countries in the coalition is not sufficient to bring SRM deployment to a level where they would profit. Accordingly, the B countries benefit from inviting C countries to join, thus preventing them from losing under SRM deployment. On the other hand, assuming that the A4 countries were not part of the coalition (i.e. only A1, B1, B2, and C countries), the weighting of economic interests in and against SRM deployment would change in such a way that the coalition would decide to forgo SRM deployment. Consequently, in line with the results from Fig. 5, there would be no incentive for the A4 countries to free-ride (even though we classified them as free-riders in Section 3.2). The A1 countries would have an incentive to keep the A4 countries in the coalition to answer the question how much SRM to do more in their favor. Accordingly, these considerations suggest that the grand coalition would appear to be a plausible solution for a cooperative SRM coalition game with externalities.

4. Discussion and conclusion

The combination of three effects determines climate engineering incentives for countries with different preferences regarding climate conditions: First, global climate engineering by means of (stratospheric) solar radiation management (SRM) affects regional (grid-cell) temperature and precipitation in a regionally uneven way. Second, temperature and precipitation affect Gross Value Added (GVA) at the grid-cell level, and the effect is described for both by an inverted U-shape relationship, implying that an optimal level of temperature and precipitation with respect to output does exist. Third, different assumptions about economic growth

and its distribution over regions, as projected by the Shared Socioeconomic Pathways (SSPs), affect—through changing country shares in global GVA—the efficient level of SRM deployment. Whereas all three effects are features of the data, their quantitative extent is uncertain. In addition, other effects like changing patterns of international trade, intangible costs arising from ecosystem degradation or species extinction, are important as well, but not included in our analysis which is restricted to considerations of economic efficiency. Our results should thus be interpreted as a qualitative illustration, rather than definite quantification, of the driving factors involved in country-specific incentives for SRM.

We find that for the globally efficient level of SRM the decisive influence stems from the region-specific economic growth projections embodied in the SSPs rather than from the regional patterns and impacts of climate change. The efficient level of SRM is proportional to the GVA-weighted mean temperature increase, which varies considerably according to the different growth projections (for equal climate-background conditions). However, SRM deployment to achieve the GVA-maximizing temperature is limited by the influence of SRM on precipitation. At some point, the benefits of moving GVA-weighted temperature closer to the temperature optimum are dominated by the losses from moving GVA-weighted precipitation further away from the precipitation optimum. Without any influence of SRM on precipitation, we observe a stronger reduction in global mean temperatures by SRM to maximize GVA. In reality, countries can be expected to take further climate variables into account—implying that their preferences for SRM deployment are probably more nuanced than in our simple model.

Yet, our model is rich enough to demonstrate that the heterogeneous economic interests concerning SRM deployment under future climate conditions are more nuanced than the mere distinction between climate-change losers and winners. For example, we identify countries with current climate conditions that are quite close to the economically optimal climate which might experience negative economic impacts from climate change, but would still face a situation where SRM deployment is overdone (from their perspective) under a global efficient regime.

We further find that countries have a strong incentive to be part of a global agreement on SRM in order to have their interests reflected in the decision about the globally efficient level of SRM deployment. Countries with a strong economic interest in cooling (high level of SRM deployment, e.g. India) and countries with a preference for no cooling (no SRM deployment, e.g. Canada) gain most from being part of such an agreement, even if they would have to pay the full cost of the inclusion of their preferences in the derivation of the efficient level in the framework of a Vickrey-Clark-Groves (VCG) mechanism. The impact of regional climate on economic output is probably not restricted to the influence of mean temperature and precipitation levels. In cases where (country-specific) optimal levels of the different climate variables are not only uncertain, but also (partly) private information, the VCG mechanism would be an instrument for achieving a truthful revelation of countries' preferences.

Though we have not modeled the coalition formation process explicitly, our results suggest that the grand coalition is a likely outcome. Yi (1997) examines coalition formation under the possibility of a negative and positive externality on outside coalitions, showing that under a negative externality the grand coalition is an equilibrium outcome (under open membership and other reasonable assumptions regarding the partition function), whereas under a positive externality the grand coalition is not a stable outcome due to free-riding. For several countries, SRM deployment above a certain level, which may be zero SRM, is a bad, and they have an incentive to join the coalition to prevent too much SRM from being applied. On the other hand, free-riding provides only small gains in comparison with having own preferences included in the decision about the global thermostat.

Overall, it should be noted that for climate background conditions projected for 2050 by global climate models and for most economic scenarios, the efficient SRM deployment levels imply an 'overcooling', which means SRM is deployed to an extent that the global mean

temperature is reduced below its average over the period between 1975 and 2005. This is partly driven by the economic convergence inherent in the SSPs, implying that currently rather poor but warm countries will gain relatively more weight in the decision on the globally efficient thermostat in future. However, it should be noted that we derive efficient SRM levels under the assumptions (a) that the optimal climate (in our analysis, the mean temperature and precipitation) is constant, and (b) that economic growth is not affected by climate change. We briefly discuss the implications of relaxing these assumptions in turn. (a) Once relatively poor and warm countries start developing, we may expect a shift from agriculture to manufacturing and the service sectors and hence reduced vulnerability to weather and climate change. At the same time, development increases adaptive capacity (Yohe and Tol, 2002; Adger, 2006). One could argue that by these effects (already implicitly captured by the growth convergence assumption in the SSPs) not only the weighted temperature but also the optimal temperature will rise, implying that the temperature gap (the difference between actual and optimal temperature) will increase at a lower rate than under the assumption of a constant optimal temperature. In turn, efficient SRM levels would decrease. (b) If we allowed climate change to affect economic growth, say through productivity, investment, and technological progress, we could probably not rule out a scenario in which hot countries grow at a slower rate (e.g., Moyer et al., 2014; Dietz and Stern, 2015; Moore and Diaz, 2015) and might even be trapped in poverty (Tol, 2018). Under the assumption that climate change negatively (positively) affects growth rates in warm (cold) countries, global warming has less of an upward effect on GVA-weighted temperature than on mean temperature – the former could even fall. Accordingly, in a static decision framework, the efficient level of SRM could drop because the relative contribution of warm countries to global economic output decreases, while in a dynamic framework anticipating the reduced growth effects, the efficient level of SRM might rise. These considerations point to limitations of a static framework. Future research should extend

the present analysis to a dynamic analysis including also emission abatement as a further control variable. Furthermore, distributional concerns are critical for assessing the consequences of climate change and climate policies. The common approach is to maximize a global social welfare function that embodies inequity aversion with respect to consumption possibilities of different countries. When determining the welfare-optimal climate regime, poor countries thus get a higher relatively weight than their share in global GVA (Tol, 2010). As the poor countries tend to face warmer climate conditions, for the scenarios with low growth convergence we would expect that the welfare-optimal temperature increase would be lower than the globally efficient temperature increase. Overall, we would thus expect a smaller spread in the welfare-optimal levels of SRM deployment across scenarios. However, we restricted our analysis to considerations of economic efficiency. We see this as a first step towards characterizing a global welfare-optimum, which should complement the measures to achieve a global efficient climate by policies that (re-)distribute consumption possibilities across (and perhaps within) countries, such as the USD 100 billion goal of climate finance included in the Paris agreement. Such considerations of international politics go beyond the present paper.

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Appendix A. Estimating $T_j(R,S)$ and $P_j(R,S)$

To estimate the influence of S and R by using the HadCM3L general circulation model, we relied on a standard emissions scenario (SRES A1B) to represent future trajectories for GHG concentrations and tropospheric aerosol emissions, and considered multiple trajectories for stratospheric SRM. The changes were computed against a 2005 observational baseline (to be in line with the temperature and precipitation data in Nordhaus, 2006). The analysis uses then six decades of output from three SRM scenarios. Each scenario is represented by the decadal mean values from three initial condition ensemble members. Simulation output was regridded to a 1 degree resolution to correspond with the G-Econ dataset. We fitted a linear model to predict changes in temperature and precipitation as a function of greenhouse gas forcing (in W/m²), tropospheric aerosol forcing (in W/m²), and solar radiation management (in units of stratospheric aerosol optical depth*1000) at each grid cell.

Appendix B. Estimating $GCP(T_j, P_j)$

We estimated changes in GCP as function of grid cell temperature and precipitation with a cross-section estimation, using average grid-cell temperature and precipitation (over the period 1975 until 2005) as explanatory variables. The data, including also other geographic control variables like the distance to the coast or elevation, are obtained from the G-Econ database (Nordhaus, 2006). The 1-degree latitude by 1-degree longitude grid cells are assigned to countries proportionally to the area of the country in the grid-cell, yielding a total number of 16,082 GCP observations. Accordingly, following Nordhaus (2006) we estimated

$$\ln(GCP_{ij}) = a_0 + a_1 T_j + a_2 T_j^2 + a_3 P_j + a_4 P_j^2 + c_i + \sum_{k=5}^7 a_k G_{kij} + \sum_{k=8}^{13} a_k D_{kj} + \epsilon_{ij} \quad (B.1)$$

where GCP_{ij} is gross cell product in 2005 USD (at market exchange rates), c_i captures country fixed effects, G_k are two geographic variables (accounting for elevation and area of the grid cell in country i), D_k are six dummy variables (accounting for being in the high latitudes, for different distances to the coast (three dummy variables), and accounting for extreme rich cells (two dummy variables), and ϵ_{ij} is the error term. We estimated eq. (B.1) by weighted least squares using the inverse standard deviation of gross cell product as weights. We relied on Newey-West-based determination for the coefficient covariance matrix. The regression results are listed below. The regression results of the alternative specifications can be found in the SI in the file "Alternative_Specifications.xlsx".

Dependent Variable: LN_GVA_MIO

Method: Least Squares

Date: 05/07/20 Time: 01:14

Sample: 118842 IF D_ZEROGRID = 0

Included observations: 16082

Weighting series: LN_GVA_MIO

Weight type: Inverse standard deviation (EViews default scaling)

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 13.0000)

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	-1.841717	0.390600	-4.715100	0.0000
TEMP	0.239883	0.010856	22.09618	0.0000
TEMP_2	-0.008402	0.000437	-19.21480	0.0000
PREC	0.001045	0.000157	6.659554	0.0000
PREC_2	-2.91E-07	4.92E-08	-5.915697	0.0000
L_AREA	0.828587	0.035449	23.37383	0.0000
D_SHORT	0.416191	0.066168	6.289946	0.0000
D_MED	0.368799	0.081012	4.552375	0.0000
D_LONG	0.390979	0.060201	6.494508	0.0000
D_LAT	-0.281030	0.137875	-2.038293	0.0415
ELEV_SRTM_PRED	-0.000356	4.97E-05	-7.162032	0.0000
D_RICH_1	2.318679	0.239533	9.680000	0.0000
D_RICH_2	1.051876	0.304123	3.458723	0.0005
CD_ALBANIA	-1.633659	0.375165	-4.354506	0.0000
CD_ALGERIA	-1.585341	0.496443	-3.193401	0.0014
CD_ANGOLA	-2.972047	0.474531	-6.263120	0.0000
CD_ARGENTINA	-1.892056	0.354914	-5.331023	0.0000
CD_ARMENIA	-0.081149	0.378279	-0.214523	0.8301
CD_AUSTRALIA	-2.084722	0.509631	-4.090648	0.0000
CD_AUSTRIA	-0.696083	0.383690	-1.814180	0.0697
CD_AZERBAIJAN	-0.349761	0.280336	-1.247650	0.2122
CD_BAHAMAS	-0.229478	0.690727	-0.332227	0.7397
CD_BANGLADESH	0.647664	0.320075	2.023479	0.0430
CD_BELARUS	-0.758523	0.341590	-2.220564	0.0264
CD_BELGIUM	-1.127613	0.287567	-3.921213	0.0001
CD_BELIZE	-2.255010	0.283910	-7.942691	0.0000
CD_BENIN	-1.676492	0.383326	-4.373541	0.0000
CD_BHUTAN	-1.436489	0.297820	-4.823346	0.0000
CD_BOLIVIA	-2.325931	0.611592	-3.803074	0.0001
CD_BOSNIA_HERZEG	-1.340540	0.309590	-4.330046	0.0000
CD_BOTSWANA	-2.027444	0.834717	-2.428899	0.0152
CD_BRAZIL	-1.470200	0.380735	-3.861478	0.0001
CD_BULGARIA	-3.964291	0.375307	-10.56280	0.0000
CD_BURKINA_FASO	-1.534246	0.431049	-3.559328	0.0004
CD_BURUNDI	-1.665437	0.299215	-5.566018	0.0000
CD_CAMBODIA	-1.530296	0.572971	-2.670808	0.0076
CD_CAMEROON	-1.850556	0.493491	-3.749926	0.0002
CD_CAPEVERDE	-1.068623	0.325609	-3.281922	0.0010
CD_CENTRALAFR.	-4.119243	0.504076	-8.171864	0.0000
CD_CHAD	-2.351014	0.535274	-4.392170	0.0000
CD_CHILE	-1.474337	0.510939	-2.885543	0.0039
CD_CHINA	-0.203954	0.283520	-0.719361	0.4719
CD_COLOMBIA	-0.423549	0.516416	-0.820169	0.4121
CD_CONGO	-2.712376	0.721505	-3.759329	0.0002
CD_COSTARICA	0.584440	0.440306	1.327348	0.1844
CD_COTE_IVOIRE	-1.599718	0.363496	-4.400925	0.0000
CD_CROATIA	-3.305464	0.417803	-7.911542	0.0000
CD_CYPRUS	-4.118362	0.448783	-9.176725	0.0000
CD_CZECHREPUBLIC	-1.611206	0.370417	-4.349714	0.0000
CD_DEM_REP_CONGO	-4.068576	0.440922	-9.227431	0.0000
CD_DENMARK	-1.563671	0.371893	-4.204630	0.0000
CD_DOMREPUBLIC	0.168531	0.342454	0.492128	0.6226
CD_ECUADOR	-1.171373	0.425199	-2.754883	0.0059
CD_EGYPT	-0.422010	0.853523	-0.494433	0.6210
CD_EL_SALVADOR	0.186310	0.288474	0.645846	0.5184
CD_EQUATORIALG.	-0.758002	0.278584	-2.720906	0.0065
CD_ERITREA	-3.130401	0.358786	-8.724987	0.0000
CD_ESTONIA	-3.993162	0.433346	-9.214719	0.0000
CD_ETHIOPIA	-2.471181	0.402152	-6.144901	0.0000
CD_FIJI	-1.539201	0.334433	-4.602415	0.0000
CD_FINLAND	-2.158315	0.389933	-5.535094	0.0000
CD_FRANCE	-1.582738	0.309368	-5.116043	0.0000
CD_GABON	-2.664807	0.466485	-5.712524	0.0000
CD_GEORGIA	-1.460554	0.319798	-4.567117	0.0000
CD_GERMANY	-0.538877	0.312337	-1.725306	0.0845
CD_GHANA	-1.770236	0.363843	-4.865379	0.0000
CD_GREECE	-3.076933	0.405364	-7.590538	0.0000
CD_GREENLAND	0.139522	0.409147	0.341007	0.7331
CD_GUATEMALA	-0.506322	0.558765	-0.906145	0.3649
CD_GUINEA	-2.256891	0.331807	-6.801829	0.0000
CD_GUINEA_BISSAU	-3.882421	0.309286	-12.55287	0.0000
CD_GUYANA	-3.660075	0.516852	-7.081470	0.0000
CD_HAITI	-1.343567	0.322889	-4.161084	0.0000
CD_HONDURAS	-1.257864	0.396700	-3.170818	0.0015
CD_HUNGARY	-2.244890	0.356289	-6.300759	0.0000
CD_ICELAND	-1.173625	0.687454	-1.707204	0.0878

(continued)

Variable	Coefficient	Std. error	t-Statistic	Prob.
CD_INDIA	0.458104	0.306463	1.494808	0.1350
CD_INDONESIA	-1.336379	0.434680	-3.074396	0.0021
CD_IRAN	-0.760362	0.404033	-1.881931	0.0599
CD_IRAQ	-1.022732	0.468675	-2.182179	0.0291
CD_IRELAND	-2.811123	0.449243	-6.257467	0.0000
CD_ISLAND	2.887529	0.331744	8.704081	0.0000
CD_ISRAEL	2.259523	0.418955	5.393229	0.0000
CD_ITALY	-1.466456	0.340932	-4.301311	0.0000
CD_JAPAN	1.189948	0.372918	3.190910	0.0014
CD_JORDAN	-0.592814	0.689599	-0.859650	0.3900
CD_KAZAKHSTAN	-2.254434	0.398415	-5.658505	0.0000
CD_KENYA	-1.729952	0.747058	-2.315686	0.0206
CD_KUWAIT	2.433544	0.387962	6.272643	0.0000
CD_KYRGYZTAN	-1.440819	0.322482	-4.467901	0.0000
CD_LAOS	-2.771702	0.481289	-5.758908	0.0000
CD_LATVIA	-3.981110	0.394225	-10.09858	0.0000
CD_LESOTHO	-1.748061	0.324927	-5.379862	0.0000
CD_LIBERIA	-3.798255	0.361327	-10.51197	0.0000
CD_LIBYA	-2.030060	0.625875	-3.243553	0.0012
CD_LITHUANIA	-3.251249	0.371108	-8.760918	0.0000
CD_MACEDONIA	-0.741659	0.314671	-2.356936	0.0184
CD_MADAGASCAR	-3.860689	0.392921	-9.825621	0.0000
CD_MALAWI	-2.074198	0.386253	-5.370054	0.0000
CD_MALAYSIA	0.131321	0.512809	0.256081	0.7979
CD_MALI	-2.115542	0.417609	-5.065844	0.0000
CD_MAURITANIA	-2.540520	0.461219	-5.508274	0.0000
CD_MEXICO	-0.260763	0.402929	-0.647169	0.5175
CD_MOLDOVA	-0.495433	0.440451	-1.124830	0.2607
CD_MONGOLIA	-2.490068	0.526764	-4.727107	0.0000
CD_MOROCCO	-1.382413	0.495140	-2.791965	0.0052
CD_MOZAMBIQUE	-3.260425	0.369804	-8.816621	0.0000
CD_NAMIBIA	-3.043398	0.649026	-4.689176	0.0000
CD_NEPAL	-1.085140	0.310456	-3.495307	0.0005
CD_NETHERLANDS	-0.817456	0.262170	-3.118041	0.0018
CD_NEWCALEDONIA	-1.908516	0.306133	-6.234261	0.0000
CD_NEWZEALAND	-1.739283	0.630963	-2.756555	0.0058
CD_NICARAGUA	-1.625565	0.539911	-3.010801	0.0026
CD_NIGER	-1.983234	0.469473	-4.224386	0.0000
CD_NIGERIA	-0.804164	0.418204	-1.922901	0.0545
CD_NORWAY	0.322062	0.410422	0.784709	0.4326
CD_OMAN	-0.359098	0.642501	-0.558907	0.5762
CD_PAKISTAN	0.163277	0.470141	0.347294	0.7284
CD_PANAMA	-0.820247	0.626093	-1.310103	0.1902
CD_PAPUANEWGUINEA	-3.221003	0.425423	-7.571297	0.0000
CD_PARAGUAY	-2.159504	0.628576	-3.435548	0.0006
CD_PERU	-1.307790	0.501214	-2.609244	0.0091
CD_PHILIPPINES	-0.559175	0.425971	-1.312706	0.1893
CD_POLAND	-2.159082	0.423831	-5.094204	0.0000
CD_PORTUGAL	-2.693657	0.434890	-6.193879	0.0000
CD_QATAR	1.548176	0.553747	2.795820	0.0052
CD_ROMANIA	-3.133556	0.317327	-9.874845	0.0000
CD_RUSSIA	-0.876181	0.267507	-3.275356	0.0011
CD_SAUDIARABIA	0.278506	0.384951	0.723484	0.4694
CD_SENEGAL	-1.513896	0.447052	-3.386400	0.0007
CD_SERBIA_MONT.	-1.550141	0.317573	-4.881205	0.0000
CD_SIERRA_LEONE	-2.272696	0.395657	-5.744100	0.0000
CD_SLOVAKIA	-1.826383	0.285599	-6.394913	0.0000
CD_SLOVENIA	-2.432441	0.298321	-8.153758	0.0000
CD_SOLOMON_ISLANDS	-2.624654	0.327619	-8.011303	0.0000
CD_SOUTH_AFRICA	-1.089800	0.595662	-1.829562	0.0673
CD_SOUTH_KOREA	0.836555	0.314541	2.659609	0.0078
CD_SPAIN	-2.146635	0.329763	-6.509619	0.0000
CD_SRI_LANKA	0.237355	0.397236	0.597516	0.5502
CD_SUDAN	-2.071293	0.504219	-4.107922	0.0000
CD_SURINAME	-3.138901	0.684893	-4.583051	0.0000
CD_SWAZILAND	-1.169951	0.277760	-4.212100	0.0000
CD_SWEDEN	-2.323884	0.348342	-6.671273	0.0000
CD_SWITZERLAND	3.228980	0.299021	10.79849	0.0000
CD_SYRIA	-0.579216	0.456381	-1.269150	0.2044
CD_TAJIKISTAN	-1.768619	0.268345	-6.590851	0.0000
CD_TANZANIA	-2.395148	0.333397	-7.184065	0.0000
CD_THAILAND	0.065956	0.432845	0.152378	0.8789
CD_TOGO	-1.755227	0.310842	-5.646681	0.0000
CD_TUNISIA	-0.945310	0.409231	-2.309969	0.0209
CD_TURKEY	0.000344	0.332621	0.001034	0.9992

(continued on next page)

(continued)

Variable	Coefficient	Std. error	t-Statistic	Prob.
CD_TURKMENISTAN	-2.516775	0.346579	-7.261772	0.0000
CD_UGANDA	-1.168960	0.345682	-3.381609	0.0007
CD_UKRAINE	-1.383597	0.367739	-3.762442	0.0002
CD_UNITEDARAB.	2.122035	0.397342	5.340575	0.0000
CD_UNITEDKINGDOM	-1.832784	0.487462	-3.759850	0.0002
CD_UNITEDSTATES	0.753746	0.291669	2.584256	0.0098
CD_URUGUAY	-1.984060	0.390994	-5.074399	0.0000
CD_UZBEKISTAN	-1.084730	0.584741	-1.855061	0.0636
CD_VANUATU	-2.863603	0.303836	-9.424840	0.0000
CD_VENEZUELA	-0.419236	0.595568	-0.703927	0.4815
CD_VIETNAM	-1.194809	0.473161	-2.525163	0.0116
CD_YEMEN	-1.327415	0.685937	-1.935187	0.0530
CD_ZAMBIA	-3.328380	0.475503	-6.999699	0.0000
CD_ZIMBABWE	-2.303941	0.398012	-5.788627	0.0000

Weighted statistics

R-squared	0.507647	Mean dependent var	6.018723
Adjusted R-squared	0.502574	S.D. dependent var	5.926850
S.E. of regression	1.522910	Akaike info criterion	3.689331
Sum squared resid	36,915.60	Schwarz criterion	3.768183
Log likelihood	-29,500.91	Hannan-Quinn criter.	3.715404
F-statistic	100.0696	Durbin-Watson stat	0.679751
Prob(F-statistic)	0.000000	Weighted mean dep.	6.277848
Wald F-statistic	94.45396	Prob(Wald F-statistic)	0.000000

Unweighted statistics

R-squared	0.476057	Mean dependent var	4.559587
Adjusted R-squared	0.470659	S.D. dependent var	2.579433
S.E. of regression	1.876688	Sum squared resid	56,059.01
Durbin-Watson stat	0.566728		

Table B.T1 below shows the differences across different specifications with respect to the inclusion of cell area and the inclusion of a dummy variable

Table B.T1

Differences in optimal temperature and precipitation increase across the different specifications.

Dependent variable	Specification	Optimal D temp in °C	Optimal D precip mm/m ² /year	Opt SRM (average*) W/m ²	D weighted T in SSP5 wo SRM in °C	Standard error of estimation
ln(GVA)	w ln(area)	1.49[0.47]	979 [58.42]	3.72[1.78]	2.53	283.97
	w D_Lat					
ln(GVA/area)	w ln(area)	1.59[0.45]	975 [56.31]	3.27[1.80]	2.59	287.21
	w/o D_Lat					
ln(GVA/area)	w D_Lat	1.49[1.00]	1003 [127.4]	3.91[1.77]	2.54	306.10
	w/o D_Lat	1.70[0.98]	981[121.58]	3.40[1.78]	2.49	308.39

* Average over the 50 scenarios.

for latitude.

Appendix C. Efficient level of SRM

Table C.T1 and C.T2 show the efficient level of SRM in 2050 for the different combinations of growth projections and climate projections across the SSP in 2050 for an operational cost of SRM of USD 45 bn(USD/yr)/(W/m²) and 5 bn(USD/yr)/(W/m²), respectively.

Table C.T1

Efficient SRM levels in W/m² in 2050 for operational cost of USD 45 bn(USD/yr)/(W/m²) where O and I indicate the OECD and IIASA growth projections, respectively.

Climate/economy	SSP1	SSP2	SSP3	SSP4	SSP5	Mean [Std.]
O-SSP1	6.04	6.14	6.38	6.52	7.44	6.50[0.50]
O-SSP2	3.90	4.01	4.25	4.39	5.33	4.38[0.51]
O-SSP3	3.21	3.32	3.56	3.70	4.65	3.69[0.51]
O-SSP4	1.64	1.74	1.99	2.12	3.07	2.11[0.51]
O-SSP5	5.87	5.97	6.21	6.35	7.27	6.33[0.50]
I-SSP1	3.14	3.25	3.50	3.62	4.54	3.61[0.49]
I-SSP2	2.46	2.57	2.82	2.94	3.86	2.93[0.50]
I-SSP3	3.68	3.79	4.03	4.16	5.08	4.15[0.49]
I-SSP4	0.09	0.19	0.44	0.57	1.49	0.56[0.50]
I-SSP5	2.49	2.60	2.84	2.97	3.89	2.96[0.50]
Mean[Std.]	3.25[1.71]	3.36[1.71]	3.60[1.70]	3.73[1.70]	4.66[1.70]	3.72[1.78]

Table C.T2Efficient SRM levels in W/m^2 in 2050 for operational cost of USD 5 bn(USD/yr)/(W/m^2) where O and I indicate the OECD and IIASA growth projections, respectively.

Climate/economy	SSP1	SSP2	SSP3	SSP4	SSP5	Mean[Std.]
O-SSP1	6.38	6.48	6.71	6.85	7.77	6.84[0.49]
O-SSP2	4.26	4.37	4.61	4.75	5.69	4.74[0.51]
O-SSP3	3.66	3.76	4.01	4.14	5.09	4.13[0.51]
O-SSP4	1.92	2.03	2.27	2.41	3.36	2.40[0.51]
O-SSP5	6.14	6.24	6.48	6.61	7.54	6.60[0.50]
I-SSP1	3.44	3.55	3.79	3.92	4.84	3.91[0.49]
I-SSP2	2.77	2.87	3.12	3.25	4.17	3.24[0.50]
I-SSP3	4.12	4.23	4.47	4.60	5.52	4.59[0.49]
I-SSP4	0.37	0.47	0.72	0.85	1.78	0.84[0.50]
I-SSP5	2.72	2.83	3.08	3.20	4.12	3.19[0.50]
Mean[Std.]	3.58[1.72]	3.68[1.72]	3.93[1.72]	4.06[1.72]	4.99[1.72]	4.05[1.79]

Table C.T3 shows the efficient level of SRM for the different economic scenarios in 2050 from the SSPs (i.e. for both growth assumptions) for a climate defined by the SSP5 baseline scenario. The latter implies that the unweighted temperature increase is equal across all scenarios. Table C.3 also displays the corresponding changes in mean temperature change and GVA weighted mean temperature change with and without SRM deployment.

Table C.T3

Weighted and unweighted temperature change without and with efficient SRM for the different economic scenarios in 2050 for climate background conditions as given by SSP5.

Economic scenario	dwT SRM = 0 in °C	dwT SRM* in °C	dT SRM = 0 in °C	dT SRM* in °C	SRM* (W/m^2)
IIASA-SSP4	1.99	1.67	2.10	1.26	1.49
OECD-SSP4	2.26	1.72	2.10	0.50	3.07
IIASA-SSP5	2.42	1.80	2.10	0.11	3.89
IIASA-SSP2	2.43	1.81	2.10	0.12	3.86
OECD-SSP3	2.48	1.78	2.10	-0.26	4.65
IIASA-SSP1	2.53	1.84	2.10	-0.20	4.54
OECD-SSP2	2.58	1.82	2.10	-0.58	5.33
IIASA-SSP3	2.68	1.92	2.10	-0.46	5.08
OECD-SSP5	2.80	1.89	2.10	-1.52	7.27
OECD-SSP1	2.86	1.90	2.10	-1.60	7.44

Table C.T4Efficient SRM levels in W/m^2 in 2050 for operational cost of USD 45 bn(USD/yr)/(W/m^2) and $\ln(gva)$ as dependent variable without controlling for high latitudes.

Climate/economy	SSP1	SSP2	SSP3	SSP4	SSP5	Mean[Std.]
O-SSP1	5.67	5.77	6.01	6.14	7.07	6.13[0.56]
O-SSP2	3.41	3.52	3.76	3.90	4.85	3.89[0.57]
O-SSP3	2.69	2.79	3.04	3.18	4.13	3.17[0.57]
O-SSP4	1.12	1.23	1.47	1.61	2.56	1.60[0.57]
O-SSP5	5.47	5.58	5.82	5.95	6.88	5.94[0.56]
I-SSP1	2.67	2.77	3.02	3.15	4.07	3.14[0.56]
I-SSP2	1.97	2.08	2.33	2.46	3.38	2.44[0.56]
I-SSP3	3.23	3.34	3.58	3.71	4.63	3.70[0.56]
I-SSP4	0	0	0	0.08	1.00	0.22[0.44]
I-SSP5	1.99	2.10	2.35	2.48	3.40	2.46[0.56]
Mean[Std.]	2.82[1.76]	2.92[1.78]	3.14[1.82]	3.27[1.84]	4.20[1.83]	3.27[1.80]

Table C.T5Efficient SRM levels in W/m^2 in 2050 for operational cost of USD 45 bn(USD/yr)/(W/m^2) and $\ln(gva/area)$ as dependent variable with controlling for high latitudes.

Climate/economy	SSP1	SSP2	SSP3	SSP4	SSP5	Mean[Std.]
O-SSP1	6.18	6.28	6.51	6.65	7.56	6.63[0.55]
O-SSP2	4.12	4.23	4.47	4.61	5.54	4.59[0.56]
O-SSP3	3.46	3.57	3.81	3.95	4.90	3.94[0.57]
O-SSP4	1.86	1.97	2.21	2.35	3.29	2.34[0.57]
O-SSP5	5.99	6.10	6.33	6.47	7.38	6.45[0.55]
I-SSP1	3.37	3.48	3.72	3.85	4.76	3.84[0.55]
I-SSP2	2.65	2.75	3.00	3.12	4.04	3.11[0.55]
I-SSP3	3.83	3.93	4.18	4.31	5.22	4.29[0.55]
I-SSP4	0.29	0.39	0.64	0.77	1.69	0.76[0.56]
I-SSP5	2.73	2.83	3.08	3.21	4.12	3.19[0.55]
Mean[Std.]	3.45[1.77]	3.55[1.77]	3.79[1.76]	3.93[1.77]	4.85[1.76]	3.91[1.77]

Table C.T6Efficient SRM levels in W/m^2 in 2050 for operational cost of USD 45 bn(USD/yr)/(W/m^2) and $\ln(\text{gva}/\text{area})$ as dependent variable without controlling for high latitudes.

Climate/economy	SSP1	SSP2	SSP3	SSP4	SSP5	Mean[Std.]
O-SSP1	5.72	5.82	6.06	6.19	7.12	6.18[0.56]
O-SSP2	3.58	3.68	3.93	4.06	5.01	4.05[0.57]
O-SSP3	2.90	3.01	3.25	3.39	4.34	3.38[0.57]
O-SSP4	1.35	1.46	1.70	1.84	2.79	1.83[0.57]
O-SSP5	5.54	5.64	5.87	6.01	6.94	6.00[0.56]
I-SSP1	2.77	2.87	3.12	3.25	4.17	3.24[0.55]
I-SSP2	2.11	2.21	2.46	2.59	3.51	2.58[0.56]
I-SSP3	3.37	3.47	3.72	3.84	4.76	3.83[0.55]
I-SSP4	0	0	0.13	0.26	1.19	0.32[0.50]
I-SSP5	2.12	2.23	2.48	2.60	3.52	2.59[0.56]
Mean[Std.]	2.94[1.75]	3.04[1.77]	3.27[1.79]	3.40[1.79]	4.33[1.79]	3.40[1.78]

Table C.T4 to C.T6 show the efficient levels of SRM show the efficient level of SRM in 2050 for the different combinations of growth projections and climate projections across the SSP in 2050 for an operational cost of SRM of USD 45 bn(USD/yr)/(W/m^2) for $\ln(\text{gva})$ as dependent variable without controlling for latitude and for $\ln(\text{gva}/\text{area})$ as dependent variable with and without controlling for latitude, respectively.

Appendix D. Distribution of marginal incentives

Table D.1 shows the number of countries in the different incentives areas and the share of global GVA of these countries when the efficient level of SRM is deployed.

Table D.1

Number of countries and share of GVA across incentive-areas for all SSPs and both growth projections.

	A1		A2		A3		A4		B1		B2		C	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%
IIASA growth projections														
SSP1	5	12.0	2	0.7	0	0	120	12.0	2	13.5	2	0.5	48	61.3
SSP2	5	11.6	1	0.5	0	0	121	11.7	2	13.4	2	0.5	48	62.4
SSP3	4	12.1	1	0.5	0	0	121	11.2	3	12.4	2	0.8	48	63.0
SSP4	4	18.9	1	0.5	0	0	125	15.5	1	0.0	0	0	48	65.1
SSP5	7	11.3	2	0.6	0	0	118	10.5	2	13.4	6	35.5	44	28.8
OECD growth projections														
SSP1	8	13.1	5	1.7	0	0	110	9.5	4	1.7	4	13.1	48	61.0
SSP2	8	11.8	2	0.7	0	0	115	10.8	4	13.8	2	0.3	48	62.6
SSP3	5	9.3	1	0.5	0	0	121	13.5	2	12.8	2	0.3	48	63.7
SSP4	5	9.0	1	0.3	1	12.5	122	13.2	0	0	2	0.3	48	64.8
SSP5	14	13.9	2	0.5	1	0.6	106	7.4	5	3.4	7	48.7	44	25.6

Appendix E. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2020.104852>.

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