A Scheme for Jointly Trading off Costs and Risks of Solar Radiation Management and Mitigation under Long-Tailed Climate Sensitivity Probability Density Distributions

Abstract

Side-effects of "solar-radiation management" (SRM) should be taken into account before society decides on its implementation as a climate policy option to alleviate anthropogenic global warming. We generalize cost-risk analysis that originally trades off expected welfare-loss from climate policy costs and the risks from transgressing climate targets to also include risks from applying SRM. In a first step of acknowledging SRM-risks, we represent global precipitation mismatch as a prominent side-effect of SRM under long-tailed probabilistic knowledge about climate sensitivity in our framework. We maximize social welfare for the following three scenarios, considering alternative relative weights of risks: temperature-risk-only, precipitation-risk-only, and both-risks. Our analysis show that in the temperature-risk-only scenario, perfect compliance with 2°C-temperature target is attained for all numerically represented climate sensitivities, a unique feature of SRM, but the 2°C-compatible precipitation corridor is violated. The precipitation-risk-only scenario shows an approximate mirror-image of this result. In addition, under equally-weighted both-risks scenario, almost 90% and perfect compliance can be achieved for the temperature and precipitation targets, respectively. Moreover, in a mitigation-only analysis, the welfare-loss from mitigation cost plus residual climate risks, compared to the no-climate-policy option, is about 2.9% (BGE) while being reduced by maximum 0.28% under a joint-mitigation-SRM analysis.

Keywords: Solar-Radiation Management, Mitigation, Cost-Risk Analysis, Climate Targets

1 Introduction

Aerosol Solar Radiation Management (SRM) came to prominence as a climate policy option through the study by Paul Crutzen (2006). SRM is defined as any deliberately large-scale manipulation of the planetary albedo to reduce the surface temperature and counteract the risks of climate change caused by greenhouse gas (GHG) emissions (Kravitz et al. 2013a; McMartin et al. 2014). Aerosol SRM is technically feasible and, compared to other climate policy options, a relatively inexpensive way to quickly offset anthropogenic global warming (Keith et al. 2000; Crutzen 2006; Matthews and Caldeira, 2007; Shepherd et al. 2009; Robock et al. 2009; Goes et al. 2011; Keith et al. 2012). Hence, SRM is supposed to be potentially a complement climate-policy to mitigating the GHG emissions (hereafter mitigation) (Barret et al. 2014; Clarke et al. 2014). However, for SRM severe potential side effects are discussed, such as climatic change in terms of precipitation patterns and ozone depletion, and regional disparities (Crutzen 2006; Tilmes et al. 2008; Bala et al. 2008; Robock et al. 2008; Lunt et al. 2008; Schmidt et al. 2012; Kravitz et al. 2013a; Kravitz et al. 2013b; Tilmes et al. 2013; Barret et al. 2014). While most studies on SRM have discussed these in mere isolation, here we start by the hypothesis that society will take decisions on SRM in weighing them off against costs and risks in view of alternative climate policy options, such as mitigation. Hence we strive for an integrated analysis of SRM and mitigation by pursuing a welfare-based portfolio approach.

In fact Smith and Rasch (2012) evaluated SRM in conjunction with mitigation for a limited set of pre-defined, RCP-inspired mitigation scenarios and asked for the role of SRM in meeting a pre-defined temperature target, depending on the degree of mitigation encapsulated in the scenario as well as climate sensitivity (linking equilibrium temperature rise and greenhouse gas concentration). They find that the contribution of SRM increases with climate sensitivity, while mitigation and SRM act as substitutes. However they would not ask for welfare optimal portfolios of mitigation and SRM.

This in turn was done by Goes et al. (2011) and Moreno-Cruz & Keith (2012) who have implemented SRM jointly with mitigation in a cost-benefit analysis (CBA), the so far axiomatically most developed decision-analytic framework. Here we follow an alternative approach in utilizing a global temperature target as entry-point for further analysis. We do so for two reasons. Firstly, some fraction of the climate economists' community thinks that currently applying CBA to the climate problem carries conceptual difficulties. So far existing deep uncertainties about the necessary global warming impact function and imprecise weighing of the costs and benefits would lead to rather non-robust results (IPCC AR5 WG-III Chapter 3: Kolstad et al. 2014; IPCC AR5 WG-III Chapter 2: Kunreuther et al., 2014). Therefore, more studies on global warming impacts and their valuation might be needed; at least to determine a probabilistic representation of the aggregate global warming impact function. Instead, compliance with an environmental target can be interpreted as an operationalization of the precautionary principle in view of deep uncertainty. Secondly, one could take temperature targets embraced at the latest Conferences of the Parties (UNFCCC 2015) as boundary conditions and ask for the cost efficient scenario to comply with this environmental boundary condition (cost effectiveness analysis, CEA). In fact, on the order of a thousand scenarios are assembled in the latest IPCC report (Clarke et al. 2014) that are based on climate targets in conjunction with CEA rather than on CBA. With this article we strive at serving those readers who acknowledge value in utilizing climate targets as entry assumption for further economic analysis.

In the following we generalize the target-concept to simultaneously cover the currently most discussed potential side-effect of SRM, and an infinitely-tailed probability density function on climate sensitivity. For this article we focus on the following side effect. SRM might perfectly or in part compensate for greenhouse gases in terms of global mean temperature, but might prove unable to do so for other climate variables such as precipitation. The underlying reason is that SRM and greenhouse gases act on the climate system through different spatial symmetries. For that reason, for several climate variables applying SRM destroys their linear scaling with global mean temperature. Hence for those, global mean temperature ceases being a good environmental proxy. For this article, we focus on global precipitation as one additional climate variable that would be detached from global mean temperature through SRM.

In order to tackle this problem, yet staying to the target concept as close as possible, Stankoweit et al. (2015) suggested not to completely switch paradigm towards a full-fledged impact analysis, but rather simply to move only one step further down the impact chain. Following them we would explicitly model global precipitation and derive an explicit target for it. This target we derive from asking, assuming a global temperature target of 2°C: "What precipitation change would a proponent of the 2°C target have accepted before SRM had ever been considered in global climate policy?" (The latter denotes a phase when the 2°C target was negotiated.) That way we derive a "2°C-compatible precipitation target".

Furthermore, due to a long-tailed probability density distribution on climate sensitivity, it is necessary to interpret global mean temperature targets probabilistically (Held et al. 2009). Target-based analyses, as assembled in Clarke et al. (2014), correspond to generic compliance probabilities as of 1/2 or 1/3. However, when future learning on climate sensitivity is included in intertemporal welfare analysis, lexicographic preferences induced by targets would induce inconsistencies. In order to resolve these conceptual problems, cost-risk analysis (CRA) was proposed by Schmidt et al. (2011) and operationalized by Neubersch et al. (2014).

CRA is a hybrid framework of CBA and CEA indeed, which is used as a decision-analytic framework that allows for including targets in an economic analysis in a dynamically self-consistent way while does not explicitly need climate damage function. CRA necessarily needs a climate target since the risk in this framework is defined as overshooting the climate target (Neubersch et al. 2014).

To the best of our knowledge, hereby for the first time we apply an integrated cost-risk analysis (CRA) of mitigation and SRM considering climate risks. We ask for the optimal mix of mitigation and SRM under probabilistic knowledge about climate sensitivity. This decision criterion is based on welfare maximizing which trades off between economic costs of climate policies, here mitigation and SRM, and the risk of transgressing the climate targets. Here we introduce two risks: the risk of temperature rise, and the risk of precipitation change. Our analysis is based on the 2°C-temperature target with 66% compliance probability, which is derived from UNFCCC's agreement 2011. The precipitation corridor is inferred such that it is compatible with the 2°C-temperature target as well as preindustrial precipitation. In our analysis, climate sensitivity is the key uncertain parameter and formally represented through a log-normal probability density distribution.

To represent the cost-risk of joint-mitigation-SRM analysis, we apply the model MIND (model of investment and technological development) (Edenhofer et al. 2005; Held et al. 2009; Lorenz et al. 2012; Neubersch et al., 2014) as an integrated energy-economy-climate model. Its climate module is upgraded in terms of the two-box climate module from DICE (Nordhaus 2008), calibrated to responses on time scales matching the residence times of carbon dioxide in the troposphere and sulphur dioxide in the stratosphere (Stankoweit et al. 2015). Generally speaking, MIND is a renewable-fossil distinguishable model based on a Ramsey-type macroeconomic growth model.

2 Methods

In order to clarify some unique concepts of CRA, we discuss the static problem. In the static minimization problem of CRA (equation 1), a convex decision problem is needed to prevent the local optima and jumping to a different regime of optimum which would not be in compliance with the value system of the proponents of temperature targets (Neubersch et al. 2014). To make sure that this is valid for any degrees of convexity of mitigation and SRM cost-functions, temperature and precipitation risk-functions absolutely need to be non-concave. Linear risk metrics are the most conservative functions we can choose which leads to a convex decision problem. For the mitigation cost $C(\mathrm{M})$, SRM cost $C(\mathrm{SRM})$, trade-off parameters β and α, risk due to high temperature $R(T)$, and risk of precipitation change $R(P)$, the static optimization problem reads:

$$\min \{C(\mathrm{M}) + C(\mathrm{SRM}) + \beta R(T) + \alpha R(P)\} \quad (1)$$

$$R(T) = \int f(\theta)\, \Phi(T-T_g)\, (T-T_g)\, \mathrm{d}\theta \quad (2)$$

$$R(P) = \int f(\theta)\, [\Phi(P-P_{ub})\, (P-P_{ub}) + \Phi(P_{lb}-P)\, (P_{lb}-P)]\, \mathrm{d}\theta \quad (3)$$

Linear risk metrics are defined as the probability of climate targets' violation proposed by Neubersch et al. (2014) for temperature risk, and we develop it for precipitation risk, which are respectively represented in equations 2 and 3; $f(\theta)$, Φ, T_g, P_{ub}, and P_{lb} respectively refer to the probability density distribution of climate sensitivity θ, the Heaviside function (0 for negative arguments and 1 otherwise), and the temperature target, upper-bound precipitation, and lower-bound precipitation. Uncertainty in climate response is a very important feature of the climate problem. To account for this facet, we consider probabilistic knowledge of climate sensitivity, which is log-normally distributed: θ ~ LN(0.973, 0.4748) (Wigley and Raper 2001) and represents a somewhat centered distribution. The sample number is 20 with equal probability within the range of 1.01°C to 7.17°C, which is chosen with the same approach as Lorenz et al. (2012).

As environmental target we choose the temperature target of 2°C maximum increase in global mean temperature anomaly with respect to pre-industrial and recognized by the UNFCCC's 15th Conference of the parties in 2010. It is noticeable that we assess temperature and precipitation on global and global-land scale, respectively. The global-land precipitation anomaly is linearly related to global mean temperature change caused by SRM and CO_2 emissions. We infer the coefficient of CO_2-induced temperature change from CO_2-quadrupling experiment in Schmidt et al. (2012). We use temperature and precipitation change within the G1 experiment of GeoMIP and CO_2-quadrupling experiment from Schmidt et al. (2012) to simply derive SRM-induced precipitation change coefficient through G1-($4\times CO_2$).

We apply a CRA-based welfare functional that would cope with SRM destroying global mean temperature as a proxy for most climate variables. In generalizing static model we readily obtain

$$\max W = \sum_{\mathrm{t=0}}^{\mathrm{t_{end}}} \sum_{s_1}^{s_{\mathrm{end}}} p_s \left[U(t,s) - \beta . R\big(T(t,s)\big) - \alpha . R(P(t,s))\right] \mathrm{e}^{-\rho t} \qquad (4)$$

In equation 4, t, s, p, U, and ρ represent time, state of the world (SOW, climate sensitivity), probability of each SOW, utility, and rate of pure time preference, respectively. β and α are trade-off parameters.

CRA makes a trade-off between the costs of reducing climate warming and the excess climate risk. Trade-off parameter shows how much important is the risk of climate change for the society (Neubersch 2014). Therefore, trade-off parameters are calibrated such that welfare is maximized with at least 66% probability (according to IPCC guidance note on uncertainty, the equivalent term is 'likely') of remaining below the 2°C-temperature target without considering further information. This is according to 17th COP to the UNFCCC that "aggregate emissions pathways consistent with having a likely chance of holding the increase in global average temperature below 2°C or 1.5°C above pre-industrial level" (UNFCCC 2011). The calibration is simulated in mitigation-only analysis excluding SRM because 2°C-temperature target is a political argument in line with mitigation. Equation 4 still leaves one degree of freedom between α and β. The larger α, the larger the relative weight precipitation has had in the making of the 2°C target. This is currently a normative choice.

We consider three scenarios accordingly, in which for two extreme cases of temperature-risk-only and precipitation-risk-only we only account for temperature risk and precipitation risk, respectively. As an in-between scenario, in both-risks scenario, we use the half of any of the calibrated parameters to weigh both risks equally.

This choice of scenarios is in order to follow a convex combination in accounting for temperature and precipitation risks in the decision profile. This means that the weight of one risk can be increased only and if only the other risk's weight is reduced. While precipitation is linearly related to temperature and its upper-bound is 2°C-compatible, in order to avoid double counting, a convex combination of the risks should be taken into account; otherwise, we would never recover 66% compliance.

$$\mathrm{R_{total}} = \sum_{\mathrm{t=0}}^{\mathrm{t_{end}}} \sum_{s_1}^{s_{\mathrm{end}}} p_{\mathrm{s}} \left[\epsilon.\,\beta.\,R\big(T(t,s)\big) + (1-\epsilon).\,\alpha.\,R\big(P(t,s)\big)\right] \mathrm{e}^{-\rho t} \tag{5}$$

Equation 5 shows the convex combination of expected discounted temperature and precipitation risks. The combination parameter is ϵ, which shows the weight of each risk from 0 to 1. Scenarios in this study show three combinations of the risks for ϵ equals 0, 1/2, and 1.

3 Results

In a joint-mitigation-SRM analysis, mitigation would be almost crowded out by SRM in the temperature- and precipitation-risk-only scenarios which can be explained through the low cost of SRM in order to reduce the climate risk (see Fig. 1). Society would experience almost no welfare-loss compared to no-climate-policy option (business as usual, BAU) in these two scenarios. In the both-risks scenario, welfare-loss due to climate-policies costs and climate risks is more than these two scenarios and about 0.28% (in terms of balanced growth equivalent, BGE) compared to BAU welfare which is quiet low compared to 2.9% in mitigation-only portfolio as it is displayed in figure 2. In the mitigation-only portfolio, mitigation cost (consumption loss relative to BAU consumption) approximately equals 1.3% (economic-related part in Fig. 2).

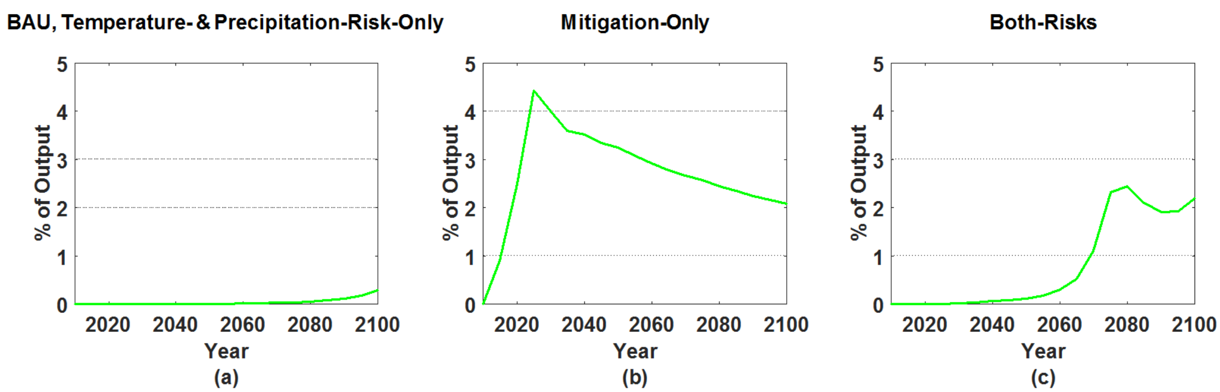

Fig 1 **Investment on renewables.** In temperature- and precipitation-risk-only scenarios, mitigation would be crowed out (a) while in both-risks scenarios (c), the starting point of investment on renewables would be about 30 years earlier than BAU analysis (a) but still 30 years later than mitigation-only analysis (b).

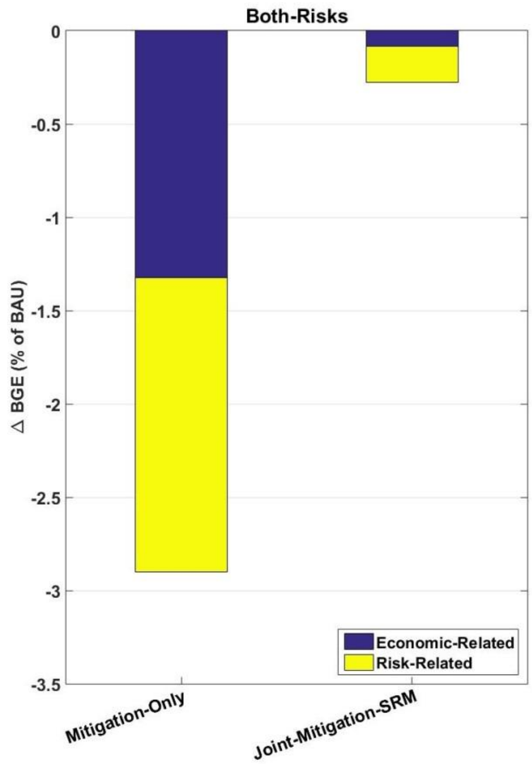

Fig 2 **Welfare-loss (in terms of BGE) in the both-risks scenario from climate risks and economic costs for the mitigation-only and joint-mitigation-SRM portfolio.** This shows that by adding SRM to the mitigation portfolio more than 90% of welfare loss due to temperature and precipitation risks and mitigation cost can be saved.

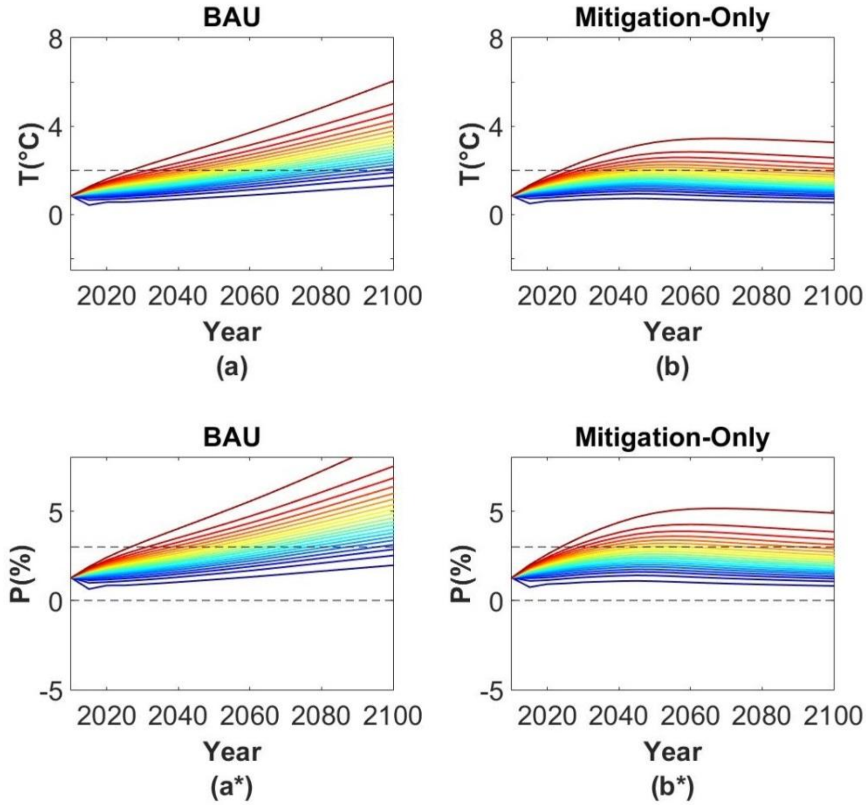

Fig. 3 **Temperature and precipitation change from preindustrial for 20 different states of the world from blue (low climate sensitivity) to red (high climate sensitivity).** Left and right graphs represent trends for BAU and mitigation-only portfolios, respectively. Dashed lines show the relevant target. In the BAU analysis, both temperature and precipitation targets would be transgressed for most of the SOWs while they comply with their targets for about 66% of SOWs in mitigation-only portfolio.

Figure 3 displays the temperature and precipitation trends for all the numerically represented climate sensitivities (SOWs) in the BAU and mitigation-only analysis in the time horizon until 2100. In the BAU analysis (Fig. 3a and 3a*), temperature target and precipitation upper bound are violated for most of the SOWs.

In the mitigation-only portfolio (Fig. 3b and 3b*), temperature and precipitation trends show a significant transgression reduction compared to BAU analysis although they would exceed their targets in 21st century for 20% upper range of SOWs in the end of century. These trends in the mitigation-only option are the same for all investigated scenarios which can be explained through the same calibration process in extreme scenarios, convex combination of risks, and compatible choice of temperature and precipitation risks when SRM is excluded. Hence, if climate sensitivity is large enough, mitigation cannot assure that temperature and precipitation remain confined to their thresholds at all times. This is where SRM might be considered as a climate policy option to help avert the 2°C transgressions.

By adding SRM to the portfolio, we again consider the temperature-risk-only, precipitation-risk-only, and both-risks scenarios (Fig. 4).

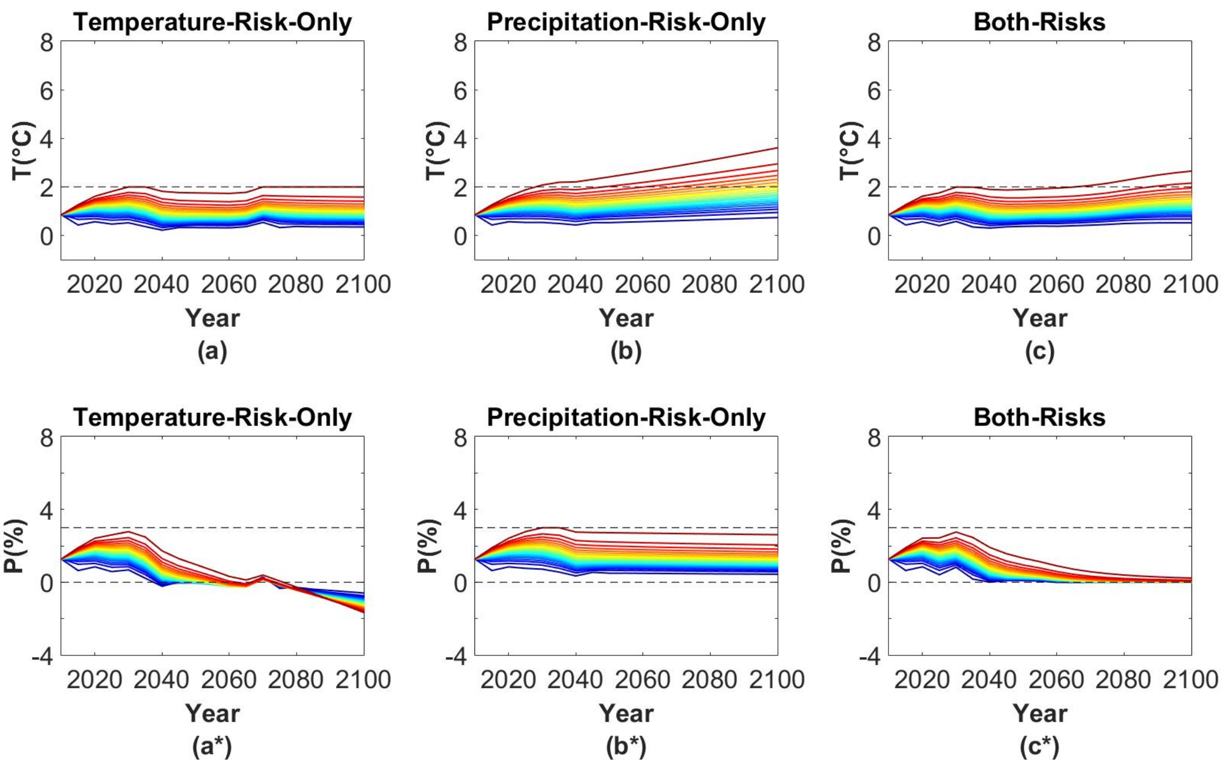

Fig. 4 **Temperature and precipitation change from preindustrial in the joint-mitigation-SRM analysis for 20 different states of the world from blue (low climate sensitivity) to red (high climate sensitivity).** Left, middle, and right graphs represent trends for temperature-risk-only, precipitation-risk-only, and both-risks. Dashed lines show the relevant target. In the temperature-risk-only scenario, perfect compliance with the temperature target can be achieved but the precipitation target is violated. The precipitation-risk-only and both-risks scenarios show perfect compliance with the precipitation target while the temperature target is transgressed.

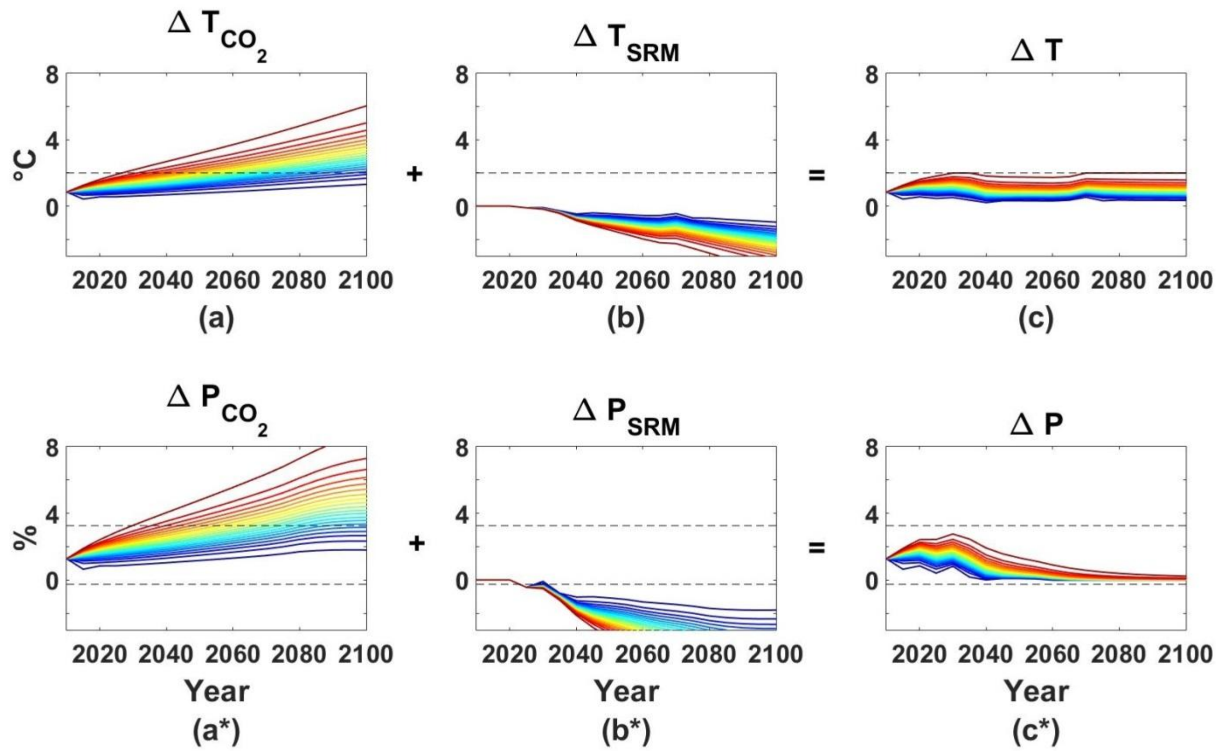

Fig. 5 **Division of temperature and precipitation changes into the CO_2- and SRM-induced changes.** Top figures divide temperature change in the temperature-risk-only scenario into the CO_2- and SRM-induced changes. Lower figures display CO_2- and SRM-induced precipitation changes in the both-risks scenario. As shown, SRM-induced changes are in a way which compensates for all the changes induced by CO_2 and so, this compensation is more for higher climate sensitivities.

Figure 4a and 4a* represent temperature-risk-only scenario, that is when SRM is added to the portfolio while its side effects is not taking into account, we get perfect compliance with the 2°C-temperature target for all the SOWs within our simulations in the current century. This is a feature impossible to achieve without SRM. The “borderline” climate sensitivity value for which a transgression would still occur is determined by equalizing the marginal welfare gain from avoiding climate risk through an extra unit of SRM, and per-unit SRM costs. The former, in turn, will depend on the properties of the probability density function of climate sensitivity. Apparently, the above borderline value of climate sensitivity is larger than our resolved upper end as of 7.17°C.

However, the precipitation violates its lower bound for all SOWs by the end of century. Precipitation declines more dramatic for those with higher climate sensitivities rather than those with lower climate sensitivities. SRM reduces the temperature risk by compensating the CO_2-induced temperature rise, which is higher for higher climate sensitivities. Therefore, SRM-induced temperature and precipitation reductions are larger when climate sensitivity is higher (see upper graphs in Fig. 5).

In contrast, in precipitation-risk-only scenario in which only the precipitation risk is activated (Fig. 4b and 4b*), the temperature guardrail is transgressed for about 35% of SOWs in a joint-mitigation-SRM analysis by the end of this century while precipitation lies on its acceptable range for all SOWs. In figure 4c and 4c*, which show the results of both-risk scenario that both precipitation and temperature risks are activated with equal weights, almost 90% and perfect compliance, respectively with temperature target and precipitation corridor, can be achieved for the time horizon until 2100. CO_2- and SRM-induced precipitation changes in this scenario are shown in figure 5 lower graphs. As both risks are taken into optimization problem in this scenario, both risks are minimized compare to the extreme scenarios.

4 Conclusions

We emphasize the need for evaluating solar radiation management (SRM) jointly with mitigation. Here we consider precipitation mismatch as a key risk category of SRM and formalize a target-based risk-cost-risk tradeoff between risks from global warming, policy costs, and risks from SRM side-effects. We choose cost-risk analysis (CRA) as our decision analytic framework as it successfully deals with both, deep uncertainty on global warming and SRM-induced damages, as well as the infinitely-tailed probability density function of climate sensitivity. CRA combines the mathematical structure of cost-benefit analysis with the target concept used in cost-effectiveness analysis. The trade-off parameters are calibrated within a universally applicable procedure, which makes a trade-off between expected welfare-loss due to mitigation costs and avoided risks of climate targets transgression considering the uncertainty in reaching the climate targets. We choose a probabilistic compliance level as of 66%, in-line with an IPCC-calibrated language adjusted interpretation of “likely” achieving the 2°C target (UNFCCC 2011).

In addition, to ask for the optimal choice between mitigation and SRM, we utilize an integrated assessment model and develop three scenarios: two as the extreme cases when either temperature risk or precipitation risk is considered named temperature-risk-only and precipitation-risk-only and one scenario which considers both risks with equal weight called both-risks scenario.

Overall, our results show that welfare-loss in mitigation-only option compared to BAU is about 2.9% (BGE) due to mitigation cost and climate risk while it is about 1.3% (BGE) only due to mitigation cost.

By adding SRM to the portfolio, in temperature- and precipitation-risk-only scenarios, welfare rises approximately to the BAU level. SRM is almost completely substituted for mitigation without significant welfare-loss in comparison with BAU which can be explained through its low cost. In the temperature-risk-only scenario, perfect compliance and perfect incompliance respectively with temperature target and precipitation corridor can be achieved for all SOWs. In precipitation-risk-only scenario, precipitation perfectly lies within its acceptable range for all SOWs, but temperature remains confined its threshold for 65% of SOWs. Results of the both-risks scenario show almost 90% and perfect compliance with temperature and precipitation targets, respectively. Although SRM is not completely substituted for mitigation in this scenario, it can save 90% of welfare loss from economic costs and climate risks.

As a note of caution we would like to highlight that we expect qualitatively different results when regional guardrails are added. In that sense the fact that mitigation is crowded out in a joint-mitigation-SRM portfolio (in temperature- and precipitation-risk-only scenarios) could be a unique feature of global guardrails, which might not be robust under regionalization. Here we merely put the idea how to generalize a single probabilistic target to multiple targets up for discussion and highlight the unique feature of SRM of achieving almost 100% compliance levels.

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