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A quantitative approach for the design of robust and cost-effective conservation policies under uncertain climate change: the case of grasshopper conservation in Schleswig-Holstein, Germany

by

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Abstract

Climate is a major determinant of the world's distribution of biodiversity and species ranges are expected to shift as the climate changes. For conservation policies to be cost-effective in the long run these changes need to be taken into account. To some extent, policies can be adapted over time, but transaction costs, lock-in effects and path dependence limit the extent to which such adaptation is possible. Thus it is desirable that conservation policies be designed so that they are cost-effective in the long run even without future adaptations. Given that the future climate change is highly uncertain, the policies need to be robust to climatic uncertainty. In this paper we present an approach for the robustness analysis with regard to the cost-effectiveness of conservation policies in the face of uncertain climate change. The approach is applied to the conservation of a grasshopper species in the German federal state of Schleswig-Holstein. For the assessment of the cost-effectiveness of considered policies we develop a climate-ecological-economic model. We show that in the near future all considered policies have a similar level of robustness, while in the more distant future the policies differ substantially in their robustness and a trade-off emerges between the expected performance and robustness of a policy.

Highlights

- Uncertainty in climate change requires robust biodiversity conservation policies
- Biodiversity conservation policies should be cost-effective
- We determine robust cost-effective policies for conservation of a grasshopper species
- There is a trade-off between expected policy performance and robustness

Key words

biodiversity conservation, climate-ecological-economic modelling, ecological-economic modelling, climate change, robustness, uncertainty, large marsh grasshopper.

1 Introduction

The spatial distribution of species and the suitability of habitats is moving in the course of climate change. On a large spatial scale the ranges of many species shift poleward or to higher altitudes (Chen et al. 2011, Bellard et al. 2012). But even on smaller scales habitat suitability changes (Varner and Dearing 2014, Peng et al. 2019). This implies that the current allocation of protected areas and conservation measures may not be able to protect the species in the future (Burns et al. 2003, Araujo et al. 2004) which needs to be considered in the development of conservation strategies (Heller and Zavaleta 2009). A particular challenge here is that the future distribution of suitable habitats for species is usually uncertain because first – due to uncertainties in the predictions of future greenhouse gas emissions and their effects on the climate – the projections of future climate change are uncertain (Kujala et al. 2013) and second, predictions of the implied climate-dependent habitat suitabilities for the species involve uncertainties (Elith et al. 2006, Bellard et al. 2012, Alagador et al. 2015). As a consequence, Jones et al. (2016) demand that in the face of climate change, spatial conservation planning must incorporate methods that are able to deal with uncertainty.

A number of approaches have been developed for the allocation of protected areas and conservation measures under climate change (Jones et al. 2016). Summers et al. (2012) and Alagodor et al. (2014) determined optimal reserve networks separately for different scenarios of climate change and contrasted them visually. Faleiro et al. (2013) predicted species presences for each potential reserve sites for a number of climate scenarios and considered in construction of the reserve network only sites that had predicted species presences above fifty percent. Kujala et al. (2013) determined optimal reserve systems, one for each of four climate scenarios, and graphically showed how each optimised policy would perform under each of the respective other three climate scenarios. A more economic approach was selected by Cavalho et al. (2011) and Loyola (2013) who considered the uncertainty in a risk-utility function, so that conservation sites with higher expected ecological benefit and/or lower climatic uncertainty are prioritised.

Often there is a trade-off between the expected ecological benefit of a site and the uncertainty in the ecological benefit. Ando and Mallory (2012) employed modern portfolio theory to select reserve sites under climatic uncertainty. Modern portfolio theory is usually employed to evaluate and rank financial investments with the task of minimising the risk in the portfolio’s total return for a given expected total return. The outcome of such an analysis is a “Pareto frontier” which contains all the combinations of expected return and risk, so that expected return can only be increased by accepting an increase in risk, or vice versa, risk can be reduced only by sacrificing expected return. Which combination of expected return and risk should be chosen depends on the degree of risk aversion in the decision maker (Eeckhoudt et al. 2005, Quaas et al. 2007), so that a risk-neutral (indifferent to risk) decision maker will prefer the investment that maximises expected return, while with an increasing level of risk aversion investments with lower expected return and lower risk are preferred.

An implicit assumption in these studies is that present allocations of conservation measures cannot be reversed in the future. Otherwise one could adapt the allocation continuously to the changing climate. While adaptive management in general is an important approach to dynamic environmental decision making under uncertainty (Arrow and Fisher 1974, Albers 1994, Costello and Polasky 2004, Kassar and Lasserre 2004), there are several obstacles to adaptive conservation management under climate change. Reallocation of nature reserves or conservation activities from one area to another, which involves restoration of that other area, is usually associated with substantial costs and uncertainties (Moilanen et al. 2009, Bull et al. 2017). Thus, once a site has been decided to be a conserved site, it is usually locked in and a chosen allocation of protected areas or conservation measures can often not been changed – a problem known as path dependence (Liebowitz and Margolis 1995, Sutherland et al. 2012, Drechsler and Wätzold 2020).

Knowing that a conservation policy that defines the areas in which conservation measures should be carried out cannot be changed in the future or only at high costs, the choice has to be made with great care. Next to Ando and Mallory's (2012) approach of minimising the uncertainty in the obtained ecological benefits for given expected benefits and deciding on the tolerable level of uncertainty, one may demand that in the presence of path dependence, chosen policies must be robust to the uncertainty. Robustness in this context means that a policy or management strategy designed under particular assumptions (e.g., with respect to future climate change) will perform at least reasonably well if those assumptions turn out to be wrong. In this manner, the criterion of robustness is related to the maximin criterion (Wald 1945) that prescribes to consider for each decision alternative the worst possible outcome and then choose the alternative that has the best out of those worst outcomes.

This concept is the basis of robustness analysis developed by Ben-Haim (2001) and applied, e.g., by Regan et al. (2005) to decision making for biodiversity conservation. Considering that the performances f_i of a set of actions $i = 1, \ldots, N$ depend on one (or several) uncertain parameter(s) v, the possible range $[v_0 - r, v_0 + r]$ of this parameters is successively increased around some baseline value v_0, and for each level of r the action i is chosen whose worst performance $\min_v f_i(v)$ within the interval $[v_0 - r, v_0 + r]$ is highest. Similar to Ando and Mallory (2012) there is a trade-off, so that an action that performs best for $r = 0$ (under certainty) will generally be outperformed by other actions for (sufficiently large) $r > 0$ (uncertainty) and vice versa.

In the present study we argue that robustness in the defined sense can be conveniently measured by a risk-utility function as it is used to model decision making under risk (Eeckhoudt et al. 2005, Quaas et al. 2007). We apply this approach to a real conservation problem and identify conservation policies that are robust to uncertainty in future climate change, in the sense that they are cost-effective over a wide range of climatic uncertainty.

The case study area is Schleswig-Holstein, the most northern of the German federal states. Much of the biodiversity in that state is located on grassland, including the large marsh grasshopper, *Stethophyma grossum*, a species of conservational concern which prefers wet meadows and marshes as habitat (Koschuh 2004) and can be considered an indicator for the quality of grasslands (Heydenreich 1999), especially extensive wet meadows (Keller et al. 2012). Like many insect species in agricultural lands, *S. grossum* relies on appropriate land use, in particular that meadows are mowed at times that do not negatively interfere with the species' life cycle (Löffler et al. 2019). The seasonal characteristics of that life cycle are likely to change with changing climate, which cannot be considered by species distribution models that are typically used to assess the response of biodiversity to climate change (Elith et al. 2006, Hannah et al. 2007, Faleiro et al. 2013, Lung et al. 2014). Instead, in the present study the impact of the changing climate is considered through a mechanistic population model (Leins et al. 2021).

The ecological model has been used by Gerling et al. (2021) to determine the cost-effective allocation of land-use measures, distinguished by different timings of mowing, that maximises the abundance of *S. grossum* in the study area for a given conservation budget. The results indicate that the cost-effective allocation of the land-use measures depends on the climatic conditions. These, however, are uncertain (Keuler et al. 2016). Two main dimensions of uncertainty may be distinguished. First, speed and intensity of the climatic change depend on the temporal path of greenhouse gas (GHG) emissions, which are highly uncertain. Second, the climate system is too complex and not all processes are sufficiently understood that a single agreed climate model exists. Instead, there are several models that address different components of the climate systems in different manners and thus provide different predictions for a given path of GHG emissions.

This uncertainty in the climate projections reflects in uncertainties about the cost-effective policy to conserve *S. grossum* in Schleswig-Holstein. The present paper proposes several conservation policies and analyses their robustness, with respect to their cost-effectiveness, against the described climatic uncertainty. In the following, the climate-ecological-economic model of Gerling et al. (2021) for the cost-effectiveness analysis of the conservation policies for a given climate trajectory is outlined, followed by a description of the applied robustness analysis. Afterwards the main results of the cost-effectiveness analyses that feed into the robustness analysis are presented as well as the results of the robustness analysis. The paper concludes with a discussion of the results and the formulation of some policy recommendations.

2 Methods

2.1 Conservation of *Stethophyma grossum* in Schleswig-Holstein

The case study region, the German federal state of Schleswig-Holstein, is located between the North and the Baltic Seas and has a maritime climate with an annual mean temperature of 8.3°C and an average annual preciptation of 789mm (DWD 2017). From its total land area of 15,800 km^2, 9,900 km^2 are used for agriculture and 3,200 km^2 are permanent grassland (Statistisches Amt für Hamburg und Schleswig-Holstein 2019).

One of the foundation's focal species is the large marsh grasshopper *S. grossum* (LMG) which inhabits wet meadows and marshes. It is an indicator for the quality of grassland habitats (Heydenreich 1999) and threatened by the intensification of land use (Miller and Gardiner 2018). Climate change is expected to have an ambivalent effect on the species, since the rising temperatures are likely to accelerate larval development and reduce mortality of larvae, while possible reductions in precipitation and soil moisture will have negative effects on the species (Poniatowski et al. 2018).

The grassland in the study region is used as meadows and pastures. Intensively used meadows are mowed up to four times a year, where the timing of a cut is when the biomass has reached 95 percent of the maximum value, so that the time between consecutive cuts is typically six weeks. Some if these cuts fall into critical phases during the LMG’s development and are detrimental for the species (Miller and Gardiner 2018). In the present study, alternative land-use measures are considered that have less adverse impacts on the LMG. These include mowing once a year before the seventh or before the ninth week after the start of the vegetation period, or mowing after the 21st or after 23rd week, or mowing once before the seventh week and a second time after the 23rd week.

2.2 The climate-ecological-economic model

In the following we briefly outline the main components of the climate-ecological-economic model which is described in detail by Gerling et al. (2021). The dynamics of the climate system are modeled to generate trajectories of relevant climatic variables. These affect the soil moisture and the vegetation dynamics. Both affect the land-use dynamics and the generated economic revenues. The climate variables, soil moisture and the land-use dynamics affect the population dynamics of the grasshopper. The model considers only grassland, representing the landscape by a square grid with a spatial resolution on 250 by 250 m^2. All input data such as soil quality have this resolution, except for the climate data which have a resolution of 12 by 12 km^2. The bio-physical parts of the model, i.e. the climate and ecological modules, run on daily time steps while the economic model has weekly time steps.

For the simulation of the climatic variables we use the regional climate model COSMO-CLM (Rockel et al., 2008, Früh et al. 2016) which is based on the weather prediction model COSMO of the German Weather Service with specific extensions by the Climate Limited-area Modelling-Community. The spatial domain of the model covers the entire European continent with the adjacent Mediterranean Sea as far as North Africa. Applications of the model to Germany can be found in Huebener et al. (2017). To generate sensible climate projections, a regional climate model like COSMO-CLM has to be coupled to a global (spatially coarser) climate model that provides spatially and temporally variable lateral boundary values (forcing data) which drive the dynamics of the regional climate model. In the present study we consider three of these global models:

- EC-EARTH operated by the Irish Centre for High-End Computing, ICHEC,
- HadGEM2-ES of the UK Met Office Hadley Centre, MOHC, and
- MPI-ESM-LR of the Max-Planck Institute for Meteorology, MPI-M.

As outlined above, the dynamics of the climate models depend on the assumed emission path of greenhouse gases (‘representative [greenhouse gas] concentration pathways – RCP’). We consider the paths RCP 2.6, RCP 4.5 and RCP 8.5 which correspond to an additional radiative forcing of 2.6 W/m^2, 4.5 W/m^2 and 8.5 W/m^2, respectively, and cover a broad range of possible climatic futures. For the subsequent simulations, the following climate variables are determined on daily time steps: mean temperature on the ground, precipitation, soil moisture content, losses of soil moisture due to evapotransporation and run-off and photosynthetically active radiation.

Based on these variables, the dynamics of the vegetation are simulated with a simplified model based on the vegetation model by Schippers and Kropff (2001) which considers the essential processes of plant mortality, biomass assimilation, allocation of biomass into roots and shoot, and mowing. Main differences to the original model is that daily time steps are subsumed into weekly time steps, the modelling of the root biomass dynamics is simplified and only the shoot biomass is simulated explicitly, mortality is modeled via a constant and a few others. To ensure credibility, the simplified vegetation model has been fitted and validated to the experimental data provided by Schippers and Kropff (2001). An important input factor to the vegetation model is the water content in the upper soil layer, with a chosen depth of 50 cm. This is calculated from the output of the climate module as described by Leins et al. (2021).

Based on the dynamics of the vegetation, for each grid cell a most profitable mowing schedule is determined that maximises the ratio of revenues and costs. Revenues are the product of the yield which takes into account the quantity and quality (energy content and digestibility) of the yield as well as the market price for concentrated feed (as an indicator for the value of the yield). The costs include, among others, labour costs and the costs of machinery use. As described in section 2.1, five alternative land-use measures are considered in which the mowing schedule is restricted to certain time periods. Under such a restriction, the timing(s) closest to the profit-maximising timing is (are) chosen. In addition, we assume that a farmer can to some extent anticipate floods in the near future that technically prohibit harvesting activities. Lastly, if the expected costs of harvesting exceed the expected revenues a cut can be cancelled altogether.

The mowing schedule on a grid cell and the dynamics of the climatic variables affect the life cycle of the LMG. Due to the complexity of the interaction, these effects are considered in a stage-and cohort-based population dynamic simulation model (Leins et al. 2021). The model considers four life stages (egg, larva, pupa and imago) where the egg stage is divided into a pre- and a post-diapause stage. Variability in the transition times between some of the stages are taken account by dividing these stages in different cohorts where each cohort comprises individuals of identical development. The two central processes in the population dynamics are the mortality of individuals and the transition from one stage to the next, which depend on the three climatic variables temperature, precipitation and soil moisture. Additionally, a harvest reduces the numbers of imagines and larvae which cannot escape from the machines.

2.3 Cost-effectiveness analysis

The climate-ecological-economic model is used to identify the cost-effective LMG conservation policy, i.e. the allocation of the land-use measures in the study region that maximises the mean number of LMG in the study region for a given budget over 20 years. For this the model dynamics are simulated for 20 years and for each year the sum of the foregone profits on the grid cells with one of the five alternative land-use measures and the total number of LMG imagines in the study region are determined.

To determine the cost-effective policy, for each grid cell the “locally cost-effective” land-use measure is identified that maximises the ratio of the number of LMG imagines and the cost in the grid cell. Having assigned to each grid cell its locally cost-effective measure, all grid cells are ordered from the highest to the lowest LMG-cost ratio and the grid cells are selected one by one until a specified budget (sum over all costs) is exhausted.

In the analysis we consider two different budget levels: one and five percent of the amount that would be necessary to apply to all grid cells their locally cost-effective land-use measure. In the cost-effective conservation policy all these selected grid cells are managed by their locally cost-effective land-use measure while all other grid cells are managed in the profit-maximising manner as outlined in section 2.2. The performance of the policy is finally measured by the mean number of LMG per Euros per year.

2.4 Robustness analysis

Climatic uncertainty is considered through five different climate scenarios that are defined by combinations of the chosen global climate model and the chosen GHG emission path (RCP):

- IC-EARTH with the three RCPs 2.6, 4.5 and 8.5
- HadGEM2-ES with RCP 4.5, and
- MPI-ESM-LR with RCP 4.5.

From the “centre” scenario, {IC-EARTH, RCP 4.5} we change the RCP “up” to 8.5 or “down” to 2.6, and for fixed RCP 4.5 we vary the climate model to HadGEM2-ES or MPI-ESM-LR.

For each of the five climate scenarios we determine the cost-effective policy considering the time interval with years 2020-2039. The five policies are termed ICHEC2.6-20, ICHEC4.5-20, ICHEC8.5-20, HadGEM-20 and MPI-20. Each of these five policies is cost-effective for the climate scenario for which it has been optimised (so, e.g., ICHEC2.6-20 is cost-effective for IC-EARTH with RCP 2.6). However, a policy optimised for one climate scenario will not necessarily be cost-effective when applied under another scenario. Following the arguments in the Introduction we understand a policy as robust if its lowest level of cost-effectiveness over all five climate scenarios is highest.

Since the deviation between the climate scenarios increases with increasing time horizon, the results of the robustness analysis are likely to depend on the considered time interval, so we consider not only the near future, 2020-2039, but also the far future, 2060-2079. As for the first time interval, we determine five cost-effective policies, denoted as ICHEC2.6-60, ICHEC4.5-60, ICHEC8.5-60, HadGEM-60 and MPI-60, each of which performs optimally for the climate scenario for which it has been optimised but most likely performs worse than other policies if it is applied in another climate scenario.

In the following we develop a simple heuristic approach for the assessment of the robustness of a policy. For this, consider that in a normal distribution with mean μ and standard deviation σ, a value of $\mu - 2\sigma$ marks about the lower 2.5%-quantile and values below $\mu - 2\sigma$ are very unlikely. Thus, if we consider a policy with uncertain performances that have a mean μ and a standard deviation σ, a value of $U = \mu - 2\sigma$ is likely to be close to the lower bound of the performances. In the Introduction we had argued that robustness in the notion of Ben-Haim (2001) relates to the maximin criterion according to which the action is chosen whose worst performance is highest. Consodering $U = \mu - 2\sigma$ as an approximation of a policy's worst performance, the maximum criterion is applied by choosing the policy whose value $U = \mu - 2\sigma$ is highest.

Why consider U rather than directly identifying the worst performances of the five policies to find their maximum? First, as outlined in the Introduction, there is a trade-off between robustness on the one hand and the expected performance (μ) of a policy on the other. In addition one could be interested in a policy that has a fairly high average performance and a fairly high level of robustness, which might be considered the policy that maximises $U = \mu - \sigma$. Since in a normal distribution, the value $\mu - \sigma$ marks about the lower 16%-quantile which is larger than the (approximated) minimum $\mu - 2\sigma$ and closer to the mean μ, maximising $U = \mu - \sigma$ is a compromise between maximising expected performance and maximising robustness. Or more generally, one can identify the policy that maximises

$$U = \mu - k\sigma \quad (1)$$

Varying k from 0 to 2 allows moving through the trade-off between maximising expected performance and maximising robustness.

The second reason for measuring robustness in the above manner is that eq. (1) is formally equivalent to a risk-utility function used in economics to model decision making under risk (Eeckhoudt et al. 2005, Quaas et al. 2007). Here $k = 0$ represents risk-neutrality (so that the decision maker does not care about the risk, σ) and increasing k represents increasing risk-aversion (so that risk σ is increasingly penalised).

To apply the described approach to the present decision problem, for each of the two time intervals we determine the performance = mean number of grasshoppers per Euro per year in the study region for each of the five policies and each of the five climate scenarios. Then for each policy we calculate the mean and standard deviation of the performances over the five climate scenarios, and via eq. (1) the risk utility U for various levels of k. The analysis is carried out for two budget levels: one percent and five percent of the maximum budget that suffices to manage the entire grassland in the study region in a grasshopper-friendly manner (cf. Gerling et al., 2021).

3 Results

Figure 1 shows that in the near future, 2020-2039, all policies except for HadGEM-20 which is the policy optimised under the HadGEM scenario for the time slice 2020-2039, perform quite similar, while HadGEM-20 is dominated for all risk-aversion levels k. For the low budget level (1% of maximum), the policy MPI-20 (blue line) has the highest expected performance, $U(k = 0)$, but a rather low robustness (small U for $k > 1$). Instead, the most robust policy is ICHEC8.5-20 (yellow line). As noted, however, the differences between the utilities (except for HadGEM-20) are rather small for all k, so the trade-off between expected performance and robustness is rather weak. A similar results is obtained for the high budget level (5% of maximum), so that except for HadGEM-20, all policies perform rather similar independent of the level of k.

For the second time interval we obtain a contrary result: for both budget levels, policies that perform well for low k perform poorly for high k and vice versa. For small $k < 0.4$, risk-utility U is maximised by ICHEC8.5-60 (yellow line), for intermediate k the best policy is ICHEC4.5-60 (green line) and for large $k > 1$ (low budget) or $k > 0.8$ (high budget) risk-utility is maximised by ICHEC2.6-60 (red line).

Altogether, while in the first time slice, 2020-2039, the ranking of the policies does not depend very strongly on the level of risk aversion k, in the second time slice, 2060-2079, we observe a trade-off, so that ICHEC8.5-60 maximises expected utility $U(k = 0)$ while ICHEC2.6-60 is the most robust policy maximising $U(k > 1)$.

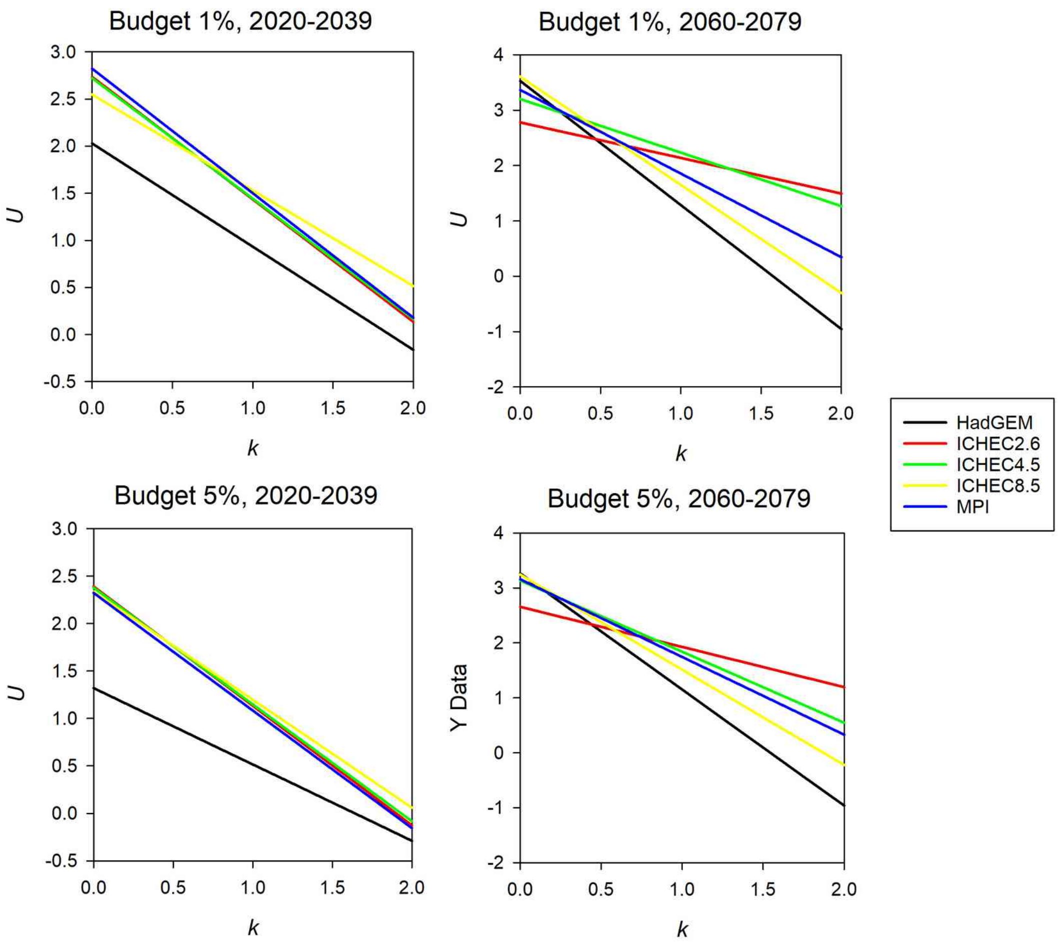

Figure 1: Risk-utility U as a function of risk aversion k for two budget levels (1% and 5% of maximum) and the two time slices, 2020-2039 and 2060-2079.

Figure 2 shows the spatial allocation of the conservation measures under these two policies for low and high budget levels. Under ICHEC2.6-60, conservation efforts (grid cells with green colour) are concentrated in the west (along the coast to the North Sea) of the study region. For the high budget level (5% of maximum) two eastern grid cells do include a high proportion of conserved land (dark green), but the majority of conservation efforts (green cells) is still in the west. In contrast, under ICHEC8.5-60 conservation efforts are more evenly allocated in the study region for the low budget level, and concentrated in the middle and the east for the high budget level.

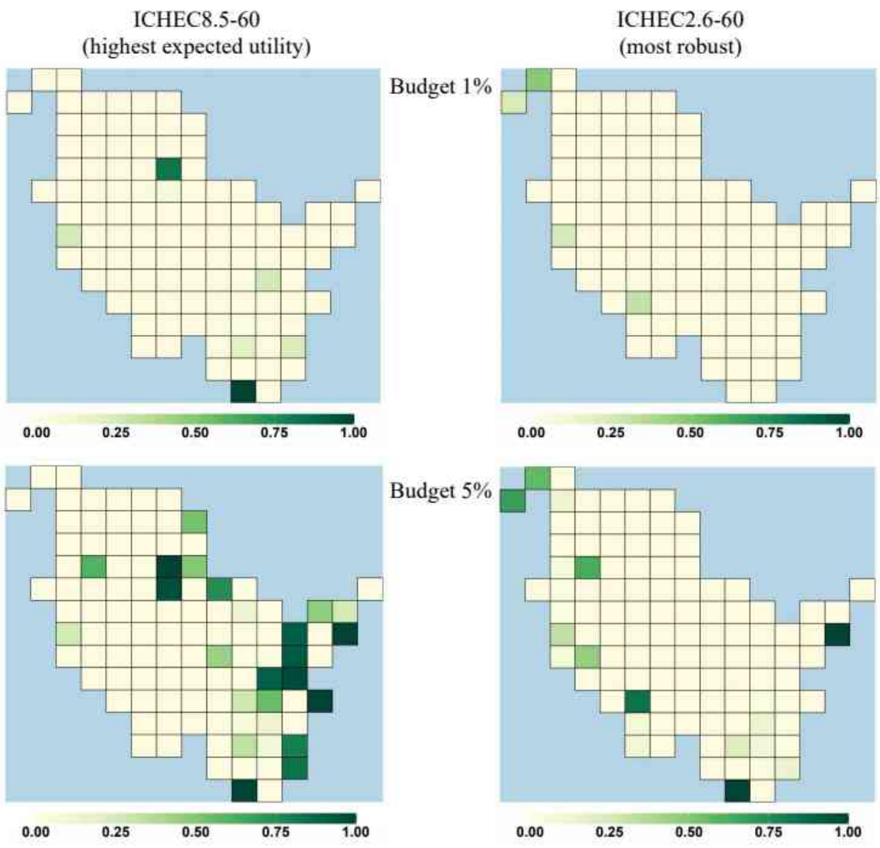

Figure 2: Proportion of grassland managed in a species-friendly manner (indicated by colour scale) per climate cell for two budget levels (1% and 5%) and for two policies (ICHEC8.5-60 and ICHEC2.6-60) for the second time interval, 2060-2079. The grids cover the entire federal state of Schleswig-Holstein.

4 Discussion

The paper analyses the robustness of policies for the conservation of *Stethophyma grossum*, a grasshopper species in Schleswig-Holstein, Germany. Robustness, in its most general sense, measures how certain one can be about the outcome of a decision in an uncertain world. In a robustness analysis, one has to specify that outcome and the uncertainty that affects it. In the present study the outcome of interest is the performance of a policy, measured by the (modeled) number of grasshoppers in the study region per Euro spent per year. Uncertainty is represented by five different climate change scenarios, each of which is based on a particular global climate model and an assumption regarding the representative concentration pathway (RCP).

The robustness of a policy with respect to the climatic uncertainty is assessed through a risk-utility function which is calculated as the expected performance of the policy minus a “risk-aversion” coefficient k times the standard deviation of the performances (eq. (1); known in decision theory as the so-called “mu-sigma principle”). Expected performance and standard deviation are taken over the five climate change scenarios.

Five policies are considered, each of which maximises the expected performance under exactly one of the five climate scenarios. The question is how well each of these polices performs if climate change turns out to follow another scenario than the assumed one. A robust policy performs reasonably well under all climate scenarios. In section 2.4 (Robustness analysis) it is argued that robustness is indicated by a high risk utility for large k.

Generally, in most portfolio optimisation problems, such as Ando and Mallory (2012), a trade-off appears between the maximisation of the expected performance (risk utility for $k = 0$) and the minimisation of the risk (standard deviation of the performances), so that the policy that maximises the risk utility for $k = 0$ will often not maximise it for other $k > 0$. In the context of robustness analysis this means that the policy with the best expected performance may not be the most robust one.

In the present study we find such a trade-off between expected performance and robustness. In the first time interval, 2020–2039 this trade-off is rather weak. The policy ICHEC8.5-20 (which was designed to maximise cost-effectiveness for the ICHEC model with RCP scenario 8.5 in the time interval 2020–2039) is outperformed by other policies for $k = 0$ and outperforms the others for large k (Fig 1, left-hand panels), but the differences in the utilities are rather small, except for policy HadGEM-20 which is strongly outperformed by the other policies for all considered k. So k has only a very little effect on the ranking of the four policies, indicating the weakness of the trade-off between expected performance and robustness.

A different result is obtained for the second time interval, 2060–2079. Here the policy ICHEC2.6-60 (which was designed to maximise cost-effectiveness in the time interval 2060–2079 for the ICHEC model with RCP scenario 2.6) has a lower expected performance ($k = 0$) than the four other policies (which have quite similar expected performances) but is the most robust one, since for all $k > 0.5$ it has the highest risk utility.

The performance differences between the policies in the second time interval are due to their different allocations of the conservation efforts (Fig. 2). Under the most robust policy, ICHEC2.6-60, conservation efforts tend to be more abundant in the west (the coast to the North Sea) than under ICHEC8.5-60 where more of the conservation efforts are allocated to the middle and the east of the study region.

Why is robustness important at all? If conservation decision can be reversed, the policies can be adapted in case the climate changes in a different manner than expected. However, it is often difficult and costly to reverse conservation decisions for several reasons. One reason may be a lack of flexibility on the side of public bodies resulting in what has been referred to as 'bureaucratic inertia' (Moe 1989). Another reason may be that NGOs and conservation foundations are prevented by high transaction costs, the statutes of agencies or local legislation to sell conserved areas and buy new ones following species range shifts in a changing climate (Gerling and Wätzold 2021). Finally, path-dependence and lock-in effects may make necessary policy adaptations slow and costly (Barnett et al. 2015, Drechsler and Wätzold 2020). In these cases, a policy based on current knowledge must lead to acceptable results even in the far future and so it should be robust against the future uncertainties.

A limitation of the present study and an avenue to further research is the restriction to only five climate change scenarios (three global models and three RCP scenarios) and a single species. Other species are likely to react different on land-use and climate change and it is important to identify conservation policies that are not only robust to climatic change uncertainty but also robust to species variability, addressing the needs of as many endangered species as possible.

5 Conclusion

The study present a useful and relatively straightforward approach for the identification of robust conservation policies in the face of climate change. While the concrete results of the analysis are specific to the study region, the general approach can be easily transferred to other regions and conservation problems. The results of such an analysis informs decision makers about the robustness of their decisions to climate uncertainty.

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