Conservation management in the face of climatic uncertainty – the roles of flexibility and robustness

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Abstract

Climate change is uncertain and has uncertain effects on the suitabilities of species habitats. Conservation strategies have to take this uncertainty into account. Two concepts for addressing uncertainty are, to make strategies adaptive and robust. Using a stylized ecological-economic model in which a decision maker can allocate a conservation budget between two time periods and two regions, I explore how the cost-effective allocation of the budget depends on ecological and economic parameters, including parameters describing the uncertain dynamics of climate change; and under which circumstances adaptive allocation strategies significantly outperform fixed strategies. Even if an adaptive strategy is politically feasible, its optimisation requires some knowledge about the dynamics of the climate change in the form of statistics like mean and variance of climate parameters. If these statistics are estimated wrong then even an adaptive strategy may fail. To explore the risk of such failure I subject the cost-effective strategies derived in the first part of the analysis to a robustness analysis that, among others, identifies those strategies that are relatively prone to wrong expectations of the climate change. Among others, the analysis reveals that flexibility pays only if there is uncertainty in the *relative* performances of different strategies; and depending on whether substitution between the benefits of the two time periods is allowed or not, the most robust strategy is to concentrate conservation expenses to the first period or to allocate the budget evenly among the two time periods, respectively.

Key words

allocation, climate change, conservation strategy, cost-effectiveness, flexibility, robustness, substitutability, uncertainty.

Highlights

- Climate change calls for adaptive and robust conservation strategies
- Cost-effective conservation strategies are identified
- The advantage of adaptive over fixed strategies is explored
- Robust conservation strategies are identified

1 Introduction

Climate change affects the spatial distribution of species and the suitability of habitats. The ranges of many species shift poleward or to higher altitudes (Parmesan et al. 1999, Root et al. 2003, Chen et al. 2011). The reason for these shifts is that previously suitable habitats become unsuitable while previously unsuitable habitats become suitable.

As a consequence, species protected in the current reserve systems will not be protected in the future (Burns et al. 2003, Araujo et al. 2004). A range of possible responses through conservation management has been compiled by Heller and Zavaleta (2009). Among their top-ranked (measured by the number of articles the authors found for each management option) are: integrate climate change into conservation planning, increase the number and sizes of reserves, protect the full range of bioclimatic variation, increase connectivity between reserves, and practice adaptive management. Jones et al. (2016) come to similar conclusions and add, among others, that methods able to deal with uncertainty need to be incorporated into spatial conservation planning under climate change.

Planning for conservation under climate change is challenging because the ranges of species and the suitability of habitats for the species will change and so do the ecological benefits of individual habitats. Furthermore, this change is uncertain (Faleiro et al. 2013) due to uncertainties in the climate projections (Kujala et al. 2013) and the ecological models that predict the implied habitat suitabilities for the species (Elith et al. 2006).

Outlining the previous research in the field, to conserve biodiversity under climate change, it is necessary to know the impact of climate change on the distribution of species and the suitabilities of potential conservation sites. Species distribution models have been used frequently to generate knowledge on this issue (Hannah et al. 2007, Faleiro et al. 2013, Lung et al. 2014). Such information can be used to prioritise sites for biodiversity conservation.

Various authors in the field of conservation planning have addressed uncertainty in the climate projections and the future suitabilities of potential conservation sites. Most papers consider this uncertainty by creating an ensemble of likely species distributions and base the reserve selection on certain averages or statistics of these ensembles, or they explicitly generate reserve networks for different scenarios (Jones et al. 2016). An explicit consideration of uncertainty is found, e.g., in Cavalho et al. (2011) and Loyola (2013) who construct some sort of risk-utility function that leads to the selection of conservation sites with higher expected ecological benefit and/or lower uncertainty.

The most explicit consideration of uncertainty is found in Ando and Mallory (2012) who employ modern portfolio theory to the selection of reserve sites under climatic uncertainty. Modern portfolio theory is a basic tool in the evaluation of financial investments. The task here is to select a portfolio of financial assets that minimises the uncertainty in the portfolio's total return for a given mean return. The assets may differ in their individual mean returns and the standard deviations of their returns, and the returns of different assets may be correlated.

While the mentioned studies contain a high level of realism and consider many specific features of their study region, the produced results and conclusions are mostly applicable only to the study area. An alternative approach is to consider stylized landscapes with only few potential sites, that can be analysed systematically to gain general insights into the problem of species conservation under climate change.

The present study is based on such a simple model. The model considers two regions that are characterised by ecological benefit and economic cost functions, i.e. functions that describe how the regional ecological benefit and the economic cost depend on the amount of area conserved. The benefit and cost functions may have different shapes and may differ between the two regions. To include climate change, a future point in time is considered and the benefit and cost functions of the two regions change between present and future in an uncertain manner.

It is assumed that a conservation agency has to allocate a financial budget over the two time periods and the two regions. The amount of money spent in a particular period in a particular region determines the current ecological benefit in that region. The objective is to maximise a joint ecological benefit composed of the benefits generated in the two time periods for the given budget (cost-effectiveness).

Uncertainty is addressed in two steps. First, I assume that although the particular shapes of the future cost and benefit functions are not known in the first time period, at least some statistics of their distributions (means, standard deviations and correlations) are known. I analyse how the cost-effective allocation strategy depends on these statistics as well as a few other model parameters.

A classical response to the described type of uncertainty is to allow for flexibility, so that (in the present setting) the allocation decision for the second time period does not have to be taken in the first time period but can be postponed to the second time period when the actual shapes of the cost and benefit functions are known. Only the decisions of how much of the total budget to spend in the first time period and where to spend this period-1 budget are taken in the first time period. Such an, the 'adaptive strategy' thus is able to adapt to the climate change and will generally outperform (and never underperform) the 'fixed strategy' in which the allocation of the period-2 budget is also taken in the first time period.

Comparing the cost-effectiveness of these allocation strategies allows assessing the value of flexibility. Flexibility is well known as a means to cope with uncertainty about the future (e.g., Arrow and Fisher (1974), Albers (1994), Dixit and Pindyck (1994), Westphal et al. (2003), Costello and Polasky (2004), Kassar and Lasserre (2004), Drechsler et al. (2006)). However, since a flexible or adaptive strategy usually involves transactions costs such as information costs and the costs incurred by the reallocation of conservation efforts, the question arises how large the efficiency gain of flexibility is, so it can be decided whether that gain is worth the additional transaction costs. Thus, next to the analysis of the cost-effective allocation of conservation efforts, the present study focuses on the question under which circumstances efficiency gains are comparatively large and when they are comparatively small.

Analyses of the type described above rely on the knowledge of the statistics (means, standard deviations and correlations) of the future change (of the cost and benefit functions, as in the present setting). This assumption may be overly optimistic and one may wonder how good a – fixed or adaptive – strategy will perform if the actual changes become manifest in a different manner than assumed in the statistics. Such a question can be addressed by robustness analysis (Ben Haim 2001, Regan et al. 2005, Salomon et al. 2020) that explores how a strategy that had been optimised with respect to certain assumptions will perform if these assumptions turn out to be wrong. Of particular interest here is to identify robust strategies that perform 'reasonably well' under a wide range of prediction errors. In the present paper I will determine the robustness of the above-mentioned fixed and adaptive allocation strategies with respect to errors in the assumptions on the climate change statistics.

2 Methods

2.1 Model description

The model assumes two regions, i = 1,2, with areas of size A_i managed for conservation. The marginal economic cost accruing from managing an area of size A_i for conservation increases linearly with increasing A_i:

$$c_i(t) = \gamma_i(t) + \mathrm{e}A_i(t), \tag{1}$$

where γ_i is a constant with respect to A_i but depends on the time period $t \in \{1,2\}$, and e is the slope of the marginal cost curve (cf. Drechsler and Wätzold 2001). For simplicity the slope e is assumed identical in both regions and does not change in time. The ecological benefit generated from a conserved area of size A_i is

$$B_i(t) = g_i(t)A_i(t)^z, \tag{2}$$

where the prefactor g_i depends on the period t, and the exponent z determines whether the ecological benefit function is convex in A_i (z > 1), linear (z = 1) or concave (z < 1) (for the ecological meaning of z, see e.g. Drechsler and Wätzold (2001)). For simplicity the exponent z is assumed identical in both regions and does not change over time.

Climate change modifies the cost and benefit functions from period 1 to period 2. For the cost functions I assume that the γ_i of eq. (1) are multiplied with some climate change factor $\delta_i^{(\gamma)}$, so that

$$\gamma_i(2) = \gamma_i(1) \cdot \delta_i^{(\gamma)} \tag{3}$$

for i = 1, 2. In an analogous manner, the benefit functions change according to

$$g_i(2) = g_i(1) \cdot \delta_i^{(g)}, \tag{4}$$

where $\delta_i^{(g)}$ represents the relative change of g_i of eq. (2) in the course of climate change.

To model uncertainty in the climate change I assume that the climate change factors $\delta_i^{(\gamma)}$ and $\delta_i^{(g)}$ are random numbers drawn from a uniform distribution with means $m_i(\delta\gamma)$ and $m_i(\delta g)$ and upper and lower bounds of $m_i(\delta\gamma)[1 \pm \sigma_i(\delta\gamma)$ and $m_i(\delta g)[1 \pm \sigma_i(\delta g)]$, respectively. In addition, the changes in the cost functions, $\delta_1^{(\gamma)}$ and $\delta_2^{(\gamma)}$, are correlated with correlation coefficient r_γ, and the changes $\delta_1^{(g)}$ and $\delta_2^{(g)}$ in the benefit functions are correlated with correlation coefficient r_g (the chosen approach for drawing correlated uniformly distributed random numbers is described in Appendix A).

Now assume a conservation agency is confronted with the task to allocate a budget C over the two time periods and the two regions, so that $C_i(t)$ is the amount of money allocated to region i in period t. Since c_i of eq. (1) is the derivative of C_i with respect to conserved area A_i, the magnitude of C_i determines the size of the conserved area A_i.

The objective of the agency is to distribute the budget such that an ecological benefit B is maximised. I assume that the benefit in each time period $t \in \{1, 2\}$ is the sum of the two regional benefits:

$$B(t) = B_1(t) + B_2(t). \tag{5}$$

For the aggregation of the two benefits $B(1)$ and $B(2)$ into a total benefit, many possibilities exist. A rather general one is

$$B = \{B(1)^{1-\alpha} + B(2)^{1-\alpha}\}^{\frac{1}{1-\alpha}} \tag{6}$$

with $\alpha \in [0, 1)$ (Quaas et al. 2013). Here $\alpha = 0$ represents full substitutability of the two benefits so that the total benefit B is the sum of $B(1)$ and $B(2)$, and a reduction in one of the two benefits can be fully compensated by an equal increase in the other benefit (cf. Fig. 1). The other extreme, $\alpha \rightarrow 1$, represents full complementarity so that a reduction in the smaller of the two benefits can not (or only marginally) be compensated by an increase in the other benefit (cf. Fig. 1).

Due to the uncertainties in the processes of climate change , for a given allocation of the budget the ecological benefit B is uncertain and has a mean m_B and a standard deviation σ_B. Risk-averse decision makers try to avoid variation and for given m_B prefer smaller σ_B to larger σ_B. I assume the conservation agency attempts to maximise, for given budget C, the risk-utility function (cf. Eckhoudt et al. 2005)

$$U = m_B - s\sigma_B, \tag{7}$$

where s is the degree of risk aversion. For $s = 0$ the standard deviation σ_B does not affect utility U, characterising the case of risk-neutrality, while increasing s reduces U if the standard deviation σ_B is non-zero.

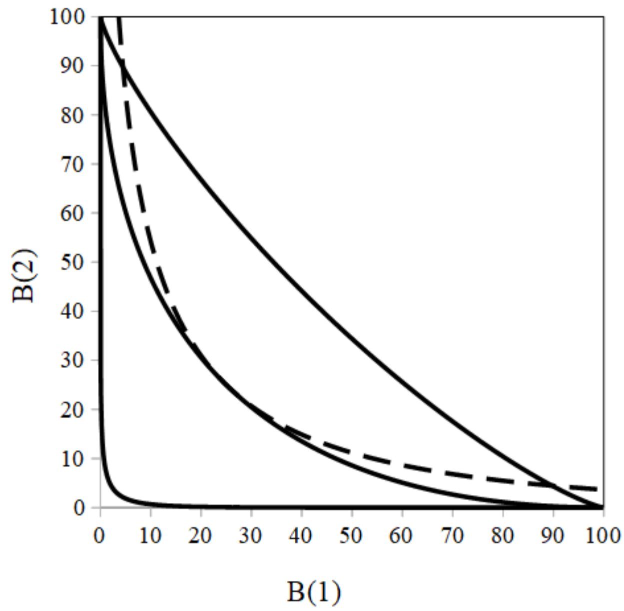

Figure 1: Iso-benefit lines, B = const. Solid lines from upper right to lower left: $\alpha = 0.2$, 0.5, 0.8; $B = 100$. Dashed line: $\alpha = 0.8$; $B = 800$.

2.2 Model analysis 1: optimisation and comparison of fixed and adaptive strategies

To determine the cost-effective allocation of the budget, the $C_i(t)$ are systematically varied in small steps. For each combination of the $C_i(t)$ ($i = 1, 2$; $t = 1, 2$) the conserved areas $A_i(t)$ are determined through the inverse of eq. (1), and the resulting benefits $B_i(t)$ are calculated through eq. (2). To take the climate and colonisation uncertainties into account, the $B_i(t = 2)$ are calculated based on 100,000 random samples of $\delta_i^{(\gamma)}$, $\delta_i^{(g)}$. The means m_B and σ_B over the resulting total benefits are taken and the allocation $C_i(t)$ that maximizes U of eq. (8) is the cost-effective one.

Two allocation strategies are analysed. In the fixed strategy all $C_i(t)$ are selected in the first time period, based among others on the means, variations and correlations of the uncertain climate change factors $\delta_i^{(\gamma)}$, $\delta_i^{(g)}$ but without knowing the exact values of the climate change factors. In the adaptive strategy the decision on the budgets $C_1(1)$ and $C_2(1)$ for the first period is the same as in the fixed strategy, i.e. in ignorance of the climate change factors $\delta_i^{(\gamma)}$, $\delta_i^{(g)}$. However, in contrast to the fixed strategy, the allocation of the remaining budget $C - C_1(1) - C_2(1)$ over the two regions in the second period (i.e., $C_1(2)$ and $C_2(2)$), is chosen only when the values of $\delta_i^{(\gamma)}$, $\delta_i^{(g)}$ and thus the precise shapes of the cost and benefit functions are known. The cost-effective adaptive strategy is determined through stochastic dynamic programming (Dixit and Pindyck 1994): For a given choice of $C_1(1)$ and $C_2(1)$, the cost-effective allocation of $C_1(2)$ and $C_2(2)$ that maximises risk-utility U is determined for each of the 100,000 random samples of $\delta_i^{(\gamma)}$, $\delta_i^{(g)}$ and the average over the obtained risk-utilities, E$U(C_1(1), \mathrm{C}_2(1))$, calculated. This average is a function of $C_1(1)$ and $C_2(1)$), and to obtain the cost-effective adaptive strategy, $C_1(1)$ and $C_2(1)$ are varied systematically and the values that maximise EU identified. The fixed and adaptive strategies are analysed for the model parameter values shown in Tables 1 and 2.

The baseline parameter values (Table 1) is chosen with the following logic. The cost and the benefit functions for both regions in the first period are assumed identical. The factors $\gamma_1(1) = \gamma_2(1)$ and $g_1(1) = g_2(1)$ are set to 1, which imposes no loss of generality. The slope of the marginal costs is set at a rather small value of $e = 0.02$, so the cost functions are only slightly convex. The benefit functions are assumed to be linear: $z = 1$. Uncertainty levels in all cost and benefit factors are moderate with $\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma) = \sigma_1(\delta g) = \sigma_2(\delta g) = 0.5$, and the cost and benefit correlations are $r_\gamma = r_g = 0$. The budget is set at a value of $C = 100$ which in preliminary analyses turned out to allows extracting the behaviour of the model. The benefit aggregation factor is set to $\alpha = 0$ which represents additive benefits. Lastly, the decision maker is risk-neutral: $s = 0$.

From these values selected model parameters are varied in turn (Table 2). The cost offset is moderately increased to $\gamma_1(1) = 1.5$ which makes conservation in region 1 more expensive. Since the model is symmetric in the two regions, increasing $\gamma_2(1)$ (or reducing either of the two factors accordingly) would lead to equivalent results. The slope of the marginal costs is increased to a moderate value of $e = 0.05$, so the cost functions are significantly convex. Analogously to the marginal cost offsets, the benefit prefactor is increased to a moderate value of $g_1(1) = 1.5$, increasing the benefit in region 1 relative to that in region 2. The shape of the benefit function is varied from linear to concave ($z = 0.5$) and to convex ($z = 2$).

Table 1: Baseline values of the model parameters.

Parameter	Notation	Equation	Value
Cost offset	$\gamma_1(1) = \gamma_2(1)$	1	1
Slope marginal cost	e	1	0.02
Benefit prefactor	$g_1(1) = g_2(1)$	2	1
Benefit exponent	z	2	1
Mean climate change factor costs	$m_1(\delta\gamma) = m_2(\delta\gamma)$	cf. eq. (3)	1
Mean climate change factor benefits	$m_1(\delta g) = m_2(\delta g)$	cf. eq. (4)	1
Cost variation	$\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma)$	cf. eq. (3)	0.5
Benefit variation	$\sigma_1(\delta g) = \sigma_2(\delta g)$	cf. eq. (4)	0.5
Correlation cost variation	r_γ	Appendix A	0
Correlation benefit variation	r_g	Appendix A	0
Budget	C		100
Benefit aggregation factor	α	6	0
Risk aversion parameter	s	7	0

Climate change can have positive or negative ecological impacts (e.g., Marqués et al. 2018) and so I assume it may positively or negatively affect the benefits in region 1, region 2 or both regions. This is considered by varying the mean climate change factors $m_1(\delta g)$ and $m_2(\delta g)$ systematically from 0.5 to 2, which is done in four steps on a geometric scale so that from one step to the next $m_i(\delta g)$ (i = 1, 2) is multiplied by a factor of of $2^{1/2} \approx 1.41$. Cost and benefit uncertainties are varied in turn to small values of $\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma) = 0.2$ and $\sigma_1(\delta g) = \sigma_2(\delta g) = 0.2$. The budget is increased to a rather large value of $C = 400$. The benefit aggregation factor is varied to $\alpha = 0.5$ which means that the total benefit is the squared sum of $B(1)^{0.5}$ and $B(2)^{0.5}$. Lastly, the level of risk aversion is increased to a moderate level of $s = 2$.

For each parameter combination the following quantities are determined: for the fixed strategy (i) the cost-effective share of the budget allocated to period 1, (ii) the cost-effective share of the period-1 budget in region 1, and (iii) the cost-effective share of the period-2 budget in region 1; for the adaptive strategy (iv) the cost-effective share of the budget in period 1, (v) the cost-effective share of the period-1 budget in region 1, and (vi) the cost-effective share of the period-2 budget in region 1; and (vii) the relative increase, (U_{adapt}-

$U_{\mathrm{fix}})/U_{\mathrm{fix}}$, in utility U (i.e., the efficiency gain) when switching from the fixed to the adaptive strategy. Note that since in the adaptive strategy the allocation of the period-2 budget is chosen adaptively in dependence of the observed climate change factors $\delta_i^{(\gamma)}$ and $\delta_i^{(g)}$, the cost-effective share of the period-2 budget in region 1 (quantity vi) is calculated as the mean over the cost-effective allocations obtained for the 100,000 random realisations of $\delta_i^{(\gamma)}$ and $\delta_i^{(g)}$.

Table 2: Varied values of the model parameters. Each model parameter, except for $m_1(\delta g)$ and $m_1(\delta g)$ which are varied systematically within their ranges, is varied from its baseline value up and/or down.

Parameter	Notation	Value
Cost offset	$\gamma_1(1)$	1.5
Slope marginal cost	e	0.05
Benefit prefactor	$g_1(1)$	1.5
Benefit exponent	z	0.5, 2
Mean climate change factor benefit 1	$m_1(\delta g)$	0.5, 0.71, 1, 1.41, 2
Mean climate change factor benefit 2	$m_2(\delta g)$	0.5, 0.71, 1, 1.41, 2
Cost variation	$\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma)$	0.2
Benefit variation	$\sigma_1(\delta g) = \sigma_2(\delta g)$	0.2
Correlation cost variation	r_γ	–0.8, 0.8
Correlation benefit variation	r_g	–0.8, 0.8
Budget	C	400
Benefit aggregation factor	α	0.5
Risk aversion parameter	s	2

The impacts of the model parameters on the seven quantities are determined in the following order. Starting from the baseline parameter combination (Table 1) the mean climate change factors $m_1(\delta g)$ and $m_2(\delta g)$ are varied systematically as indicated in Table 2. Then all alternative parameter combinations defined in Table 2 are varied in turn and for each parameter combination, as in the baseline parameter combination, the mean climate change factors $m_1(\delta g)$ and $m_2(\delta g)$ are varied systematically.

2.3 Model analysis 2: robustness analysis

Some of the parameters in Tables 1 and 2 are not subject to climate uncertainty: $\gamma_1(1)$, e, $g_1(1)$, z, C, α and s. Setting these at their base values of Table 1 plus varying them from there one by one to their values of Table 2 yields a total of nine *scenarios* (Table 3).

Table 3: Parameter values for the nine scenarios considered in the robustness analysis.

Scenario	Varied model parameter
1	Baseline (Table 1)
2	$\gamma_1(1) = 1.5$
3	$e = 0.05$
4	$g_1(1) = 1.5$
5	$z = 0.5$
6	$z = 2$
7	$C = 400$
8	$\alpha = 0.5$
9	$s = 2$

The choices for the other parameters, $m_1(\delta g)$, $m_2(\delta g)$, $\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma)$, $\sigma_1(\delta g) = \sigma_2(\delta g)$, r_γ and r_g represent *climate expectations*. Setting them at their base values plus varying them from there to the values of Table 2 (with some simplification in the considered values $m_1(\delta g)$ and $m_2(\delta g)$) yields eleven climate expectations (Table 4).

For each of the nine scenarios the following calculations are carried out. For each climate expectation, the cost-effective allocation strategy is determined together with its utility U. Then this strategy is evaluated for the ten respective other climate expectations and its utility for each climate ecpectation determined. This analysis is carried out separately for the adaptive and the fixed strategies. By this, for each scenario one can assess how each optimised (for given climate expectation) strategy performs if the climate change turns out not to follow the assumed expectation but one of the other ten climate expectations. And in particular, one can assess which strategy is most robust against the choice of a 'wrong' climate expectation.

Table 4: Parameter values for the eleven climate expectations.

Climate expectation	Varied model parameter(s)
1	Baseline (Table 1)
2	$m_1(\delta g) = 0.5$, $m_2(\delta g) = 0.5$
3	$m_1(\delta g) = 0.5$, $m_2(\delta g) = 2$
4	$m_1(\delta g) = 2$, $m_2(\delta g) = 0.5$
5	$m_1(\delta g) = 2$, $m_2(\delta g) = 2$
6	$\sigma_1(\delta\gamma) = \sigma_2(\delta\gamma) = 0.2$
7	$\sigma_1(\delta g) = \sigma_2(\delta g) = 0.2$
8	$r_\gamma = –0.8$
9	$r_\gamma = +0.8$
10	$r_g = –0.8$
11	$r_g = +0.8$

3 Results

3.1 Optimisation and comparison of fixed and adaptive strategies

As a first result it turns out that for all parameter combinations the cost-effective allocation under the fixed strategy is identical to that under the adaptive strategy, so below and in Appendix B only the cost-effective allocation under the fixed strategy will be reported. For the baseline scenario (parameters values as in Table 1) the following results are obtained.

Cost-effective allocation: For climate-change factors $m_1(\delta g) < 1$ and/or $m_2(\delta g) < 1$, so that benefits decline from period 1 to period 2, it is cost-effective to spend most of the budget in period 1, because here it generates higher benefits than in period 2 (Fig. 2a); and the period-1 budget should be spent evenly between the two regions (Fig. 2b), because the increasing marginal costs imply that an uneven allocation generates over-proportionally high costs without generating higher benefits (note that the benefit functions are linear: $z = 1$).

Conversely, for $m_1(\delta g) > 1$ or $m_2(\delta g) > 1$), i.e. temporally increasing benefits, most of the budget should be spent in period 2 (Fig. 2a); and the allocation of the period-1 budget over the two regions is not decisive because for those small budgets the cost functions appear nearly linear and for linear cost and benefit functions any allocation is cost-effective (Fig. 2b).

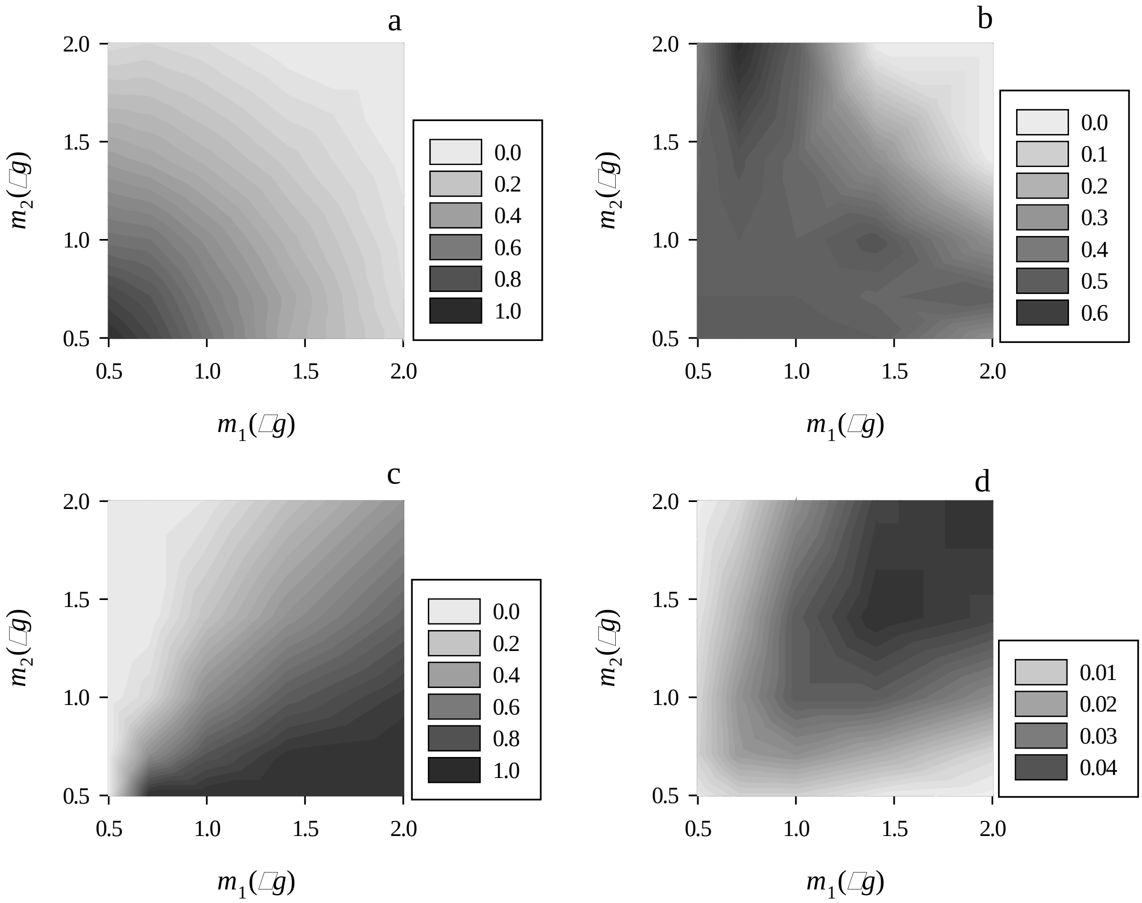

Figure 2: Cost-effective share of the budget in period 1 (panel a), cost-effective share of the period-1 budget in region 1 (panel b), cost-effective share of the period-2 budget in region 1 (panel c) and efficiency gain of the adaptive strategy compared to the fixed strategy (panel d) as functions of the mean climate change factors $m_1(\delta g)$ and $m_2(\delta g)$. Other model parameters as in the baseline scenario.

The cost-effective allocation of the period-2 budget (Fig. 2c) simply follows the ratio $m_2(\delta g)/m_1(\delta g)$: the higher the climate change factor in a given region (relative to that in the other region) the higher the budget share that region should receive.

Efficiency gain: The adaptive strategy is more cost-effective than the fixed strategy for all levels of $m_1(\delta g)$ and $m_2(\delta g)$, with a maximum efficiency gain of about five percent (Fig. 2d) for large $m_1(\delta g) \approx m_2(\delta g)$. The efficiency gain decreases with increasing dissimilarity between $m_1(\delta g)$ and $m_2(\delta g)$ and is (close to) zero if (at least) one of the two climate change factors, $m_1(\delta g)$ and $m_2(\delta g)$ is very small. The reason is that here it is obvious already in period 1 that the region i associated with the small $m_i(\delta g)$ should receive no share of the period-2 budget, so there is not much gain if that decision is postponed to period 2.

The results for the other scenarios defined by Table 2 are shown in Appendix B. A summary is given in the following list, starting with more and ending with less intuitive ones.

1. The budget should generally be allocated into the region which has the higher benefit and/or the lower cost (as, e.g., in the baseline scenario where the cost-effective budget share in period 1 declines with increasing mean climate change factors $m_1(\delta g)$ and $m_1(\delta g)$, and where the share of the period-2 budget in region 1 increases with increasing $m_1(\delta g)$).
2. Strongly increasing marginal costs and/or concave benefit functions favour a more even allocation of the budget over periods and/or among regions (as, e.g., in the cases of marginal cost slope e = 0.05 or benefit exponent z = 0.5 in which the period-1 budget should be allocated evenly among the two regions.
3. In the presence of convex benefit functions (e.g., z = 2), in contrast, the budget should be more concentrated in one period and one region.
4. If substitutability between the benefits of time periods 1 and 2 is restricted (α = 0.5) the allocation of the budget between the two time periods should be more even.
5. Higher uncertainty in the climate change factors increases the efficiency gains associated with the adaptive strategy.
6. If climate change increases especially the benefit in the region with the higher cost and/or lower initial benefit the share of the budget allocated to period 2 should be reduced because the effectiveness of budgets spent in that period is reduced (as, e.g., in the case of an increased cost in region 1, $\gamma_1(1)$ = 1.5, but higher mean climate

change factor, $m_1(\delta g) > m_2(\delta g)$; or in the case of a higher benefit factor, $g_1(1) = 1.5$, and a lower mean climate change factor, $m_1(\delta g) < m_2(\delta g)$).

7. Higher budgets imply higher marginal costs, implying that more even allocations over periods and/or among regions become cost-effective.
8. A risk-averse decision maker (risk aversion $s > 0$) will spend more of the budget in period 1 to avoid the uncertainty in the outcomes obtained in period 2.
9. The efficiency gain associated with the adaptive strategy increases with the sensitivity of the cost-effective allocation of the period-2 budget to the uncertain climate change factors, in particular the factors $\delta_1^{(g)}$ and $\delta_2^{(g)}$. In the following several cases are highlighted in which this sensitivity is particularly high or particularly low:
    a. If the mean climate change factor $m_i(\delta g)$ is higher in the region with the higher initial cost $\gamma_i(1)$, a trade-off occurs in period 2 between minimising costs per conserved area and maximising benefits per conserved area, enhancing the sensitivity of the cost-effective allocation to climate change.
    b. If the mean climate change factor $m_i(\delta g)$ is higher in the region with the lower initial benefit $g_i(1)$ it is not clear in period 1 whether it will be better to concentrate the period-2 budget in region i or not, enhancing the sensitivity of the cost-effective allocation to climate change.
    c. Concave benefit functions or strongly increasing marginal costs favour more even allocations, avoiding extreme allocations in which the period-2 budget is allocated only into one of the two regions. This reduces the sensitivity of the cost-effective allocation to the climate change factors.
    d. Convex benefit functions imply a concentration of the budget in one of the two regions. If the mean climate change factors have similar magnitudes it is difficult to predict in period 1 whether in period 2 region 1 or region 2 should be preferred, enhancing the sensitivity of the cost-effective allocation to climate change.
    e. A large positive spatial correlation between the climate change factors (in particular, a large r_g) implies that although the climate change factors ($\delta_1^{(g)}$ and $\delta_2^{(g)}$) are uncertain, they will be of similar magnitude in both regions, reducing the sensitivity of the cost-effective allocation to the climate change factors.

3.2 Robustness analysis

As described in section 2.3, for each of the eleven climate expectations of Table 4 the cost-effective fixed and adaptive strategies are determined for the baseline scenario (Tables 1, 3). The utility of these strategies then is evaluated for all eleven climate expectations of Table 4. The first row of Table 5, e.g., shows the results for the fixed strategy, termed F1, optimised for climate expectation 1. The first value in the row (84) is the utility obtained for climate expectation 1 for which the strategy F1 had been optimised for. The second value (63) is the utility obtained for the same strategy F1 under climate expectation 2. It is also the lowest utility obtained for strategy F1 under all climate expectations 1–11. The highest utility (127) of strategy F1 is obtained under climate expectation 5.

The robustness of strategy F1, i.e. its likelihood of not underperforming, is obviously positively related to the mean of the eleven utilities and negatively related to their standard deviation. The two quantities are aggregated in the second last value of the first row which gives the mean minus two standard deviations of the utilities in the first row. Since this robustness index implicitly assumes that all climate expectations are equally likely, another useful index of robustness is added in the last entry of the first row: the minimum over the eleven utilities (63). Across all scenarios and climate expectations (with scenario 1 shown in Tables 5 and 6 as an example), both robustness indices turn out to agree perfectly.

The same analysis is carried out for the other ten fixed strategies F2–F11 and the eleven adaptive strategies A1–A11. Both robustness indices are maximal for strategies F2 and A2 that were optimised for climate expectation 2 (which assumes declining benefits from time period 1 to time period 2) and thus prescribe an allocation of the entire budget into time period 1 (Fig. 2, origins of upper left panel).

The result that F2 and A2 are most robust is obtained for the other eight scenarios of Table 3. Table 7 shows the minimum utilities (cf. last column of Tables 5 and 6) for all eleven fixed strategies, F1–F11 (for the adaptive strategies the results are almost identical) for the scenarios 1–9. The highest minimum utility (‘maximin’) is always obtained with strategy F2 (grey-shaded cells in Table 7) that assumes a reduction of the benefit functions.

One should, however, be aware that the exact shape of a strategy depends on the assumed scenario. A look into the figures of Appendix B reveals that strategy F2 always prescribes an prioritisation of the budget in time period 2, but the allocation of the period-1 budget over the two regions depends, e.g., on the shapes of the cost and benefit functions in that time period (cf. Figs. B2–B6).

Table 5: Utilities for the fixed allocation strategies F1–F11 optimised for the baseline scenario (Tables 1, 3) and for each climate expectation (rows) as a function of the 'realised' climate expectation (columns). Second last column: mean minus two standard deviations of the utilities in each row. Last column: Minimum of the utilities in each row.

	1	2	3	4	5	6	7	8	9	10	11		
F1	84	63	94	96	127	84	83	84	84	84	84	59	63
F2	73	73	73	73	73	73	73	73	73	73	73	73	73
F3	67	37	126	37	126	67	66	67	67	66	66	17	37
F4	67	39	39	126	125	68	67	68	67	67	67	18	39
F5	75	37	92	95	150	75	73	75	75	74	74	30	37
F6	84	63	96	94	127	84	83	84	84	84	84	59	63
F7	84	63	94	96	127	84	83	84	84	84	84	58	63
F8	84	63	94	96	127	84	83	84	84	84	84	59	63
F9	84	64	95	95	126	84	83	84	84	84	84	59	64
F10	84	62	95	95	129	84	83	84	84	84	84	58	62
F11	84	62	95	95	129	84	83	84	84	84	84	58	62

In most scenarios (columns in Table 7) there is considerable variation in the minimum utilities over the strategies, indicating that the cost-effective strategy quite sensitively depends on the chosen climate expectation and fails under the alternative climate expectations. Exceptions are scenarios 4, 8 and 9 (grey-shaded cells in Table 7) which represent strongly increasing marginal costs (e = 0.05), restricted substitutability (α = 0.5) and risk aversion (s = 2), respectively. In the first two scenarios, 4 and 8, an even allocation of the budget over both time periods is cost-effective, regardless of the assumed climate expectation (cf. Figs. B3 and B14), so that all strategies F1– F11 are almost identical and thus perform very similarly for a given climate expectation. A similar situation is observed in scenario 9, except that here it is cost-effective, throughout all climate expectations, to spend most of the budget in time period 1 (cf. Fig. B15).

Table 6: Utilities for the adaptive allocation strategies A1–A11 optimised under the baseline scenario (analogous to Table 5).

	1	2	3	4	5	6	7	8	9	10	11		
A1	88	63	118	118	137	85	86	88	85	87	86	55	63
A2	77	73	82	82	85	77	76	77	77	77	77	72	73
A3	81	43	126	126	156	78	79	81	78	80	80	32	43
A4	82	46	126	126	155	79	81	82	79	82	81	35	46
A5	79	39	125	125	158	76	77	79	75	78	78	27	39
A6	88	65	116	116	134	85	86	88	85	87	86	57	65
A7	88	63	118	118	137	85	86	88	85	87	86	55	63
A8	88	64	117	117	135	85	86	88	85	87	86	56	64
A9	88	65	115	115	132	85	86	87	85	87	86	58	65
A10	88	64	117	117	135	85	86	88	85	87	86	56	64
A11	88	64	117	117	135	85	86	88	85	87	86	56	64

Table 7: Minimum utilities (taken over all climate expectations: cf. Table 5) of the 11 fixed strategies F1–F11. Each column gives the results for one of the nine scenarios defined in Table 3.

	1	2	3	4	5	6	7	8	9
F1	63	82	53	55	14	1987	186	122	73
F2	73	96	59	65	14	3820	204	124	73
F3	37	60	39	34	13	1988	144	112	73
F4	39	51	38	35	13	1989	144	110	73
F5	37	49	34	34	12	1986	136	116	48
F6	63	84	53	55	14	1987	186	122	73
F7	63	85	52	57	14	1988	188	122	73
F8	63	83	52	56	14	1986	186	123	67
F9	64	84	53	56	14	1987	186	122	73
F10	62	83	53	55	14	1983	188	122	73

F11	62	83	53	56	14	1986	186	122	73

4 Discussion

A stylised model is analysed in which a decision maker can allocate a budget over two time periods and two regions and where the costs and benefits of conservation differ between the regions and change over time in an uncertainty manner. The model is analysed in two steps. First, the cost-effective allocation of the conservation budget is determined as a function of various model parameters, assuming that the allocation if the period-2 budget must be decided upon already in the first time period ('fixed strategy') or can be postponed to the second time period when the current cost and benefit functions are known ('adaptive strategy').

Some of the model parameters describe characteristics that are, in the present setting, assumed to be time-invariant, such as the slope of the marginal costs and the convexity or concavity of the ecological benefit functions. A second set of model parameters describes the uncertain effects of climate change on the cost and benefit functions, such as the mean factors by which the ecological benefit functions multiply from the first to the second time period.

While in the first step of the analysis these climate change parameters are assumed to be known, in the second step it is explored how a strategy performs if it was designed cost-effectively under the assumption of a particular combination of climate change parameters ('climate expectations') but it turns out that the climate change had been better characterised by a different climate expectation. Particular focus here is on the identification of robust strategies that perform 'reasonably well' under a wide range of climate expectations.

The first analysis reveals some general conclusions, such that the cost-effective budget share falling into period 1 and the cost-effective allocation of that period-1 budget over the two regions is very similar between the fixed and the adaptive strategies. Further, the cost-effective allocation is strongly influenced by the slope of the marginal costs and the convexity or concavity of the ecological benefit functions, such that strongly increasing marginal costs and/or concave benefit functions favour an even allocation of the budget over time and regions.

Another important issue in this context is the way by which the ecological benefits of the two time periods are aggregated. In the present analysis I distinguished between perfect substitution where a low benefit in one time period can be fully compensated for by an accordingly high benefit in the other; and restricted substitution where a low low benefit in one time period can only partly be compensated for by a high benefit in the other time period. In the latter model, the cost-effective allocation of the budget turns out to be more even over the two time periods.

A converse effect is observed if the decision maker is assumed to be risk-averse, penalising high variation in the period-2 benefits due to climatic uncertainty. To reduce that uncertainty, a risk-averse decision maker will spend more of the budget in period 1 where the ecological benefits from conservation are certain. Here a trade-off exists between generating acceptably high benefits in both time periods and minimising the risk of a low total benefit.

A typical question raised in the present type of dynamic optimisation problem is under which circumstances the adaptive strategy most strongly outperforms the fixed strategy. Relating statements 5 and 9e from the list in section 3.1 points to an interesting and probably general conclusion. Although uncertainty generally increases the advantage of adaptive strategies over fixed strategies, only that component of the uncertainty counts which determines the *relative* favourabilities of the decisions to be made. While a high spatial correlation in the climate change factors does increase the uncertainty in the total benefit that can be attained in period 2, it reduces the uncertainty in the *relative* magnitudes of the climate change factors (in particular the uncertainty in the ratio $\delta_1^{(g)}/\delta_2^{(g)}$) – and thus reduces the advantage of adaptive strategies.

Summarising the results of the second analysis, the most robust strategy – regardless of whether fixed or adaptive – is the strategy that expects a decline in the ecological benefits over time and concentrates that budget in the first time period. This is even for moderate restriction of substitutability (scenario 8 in Table 7). However, in that scenario the strategies F1 and F6–F11 (cost-effective for climate expectations 1 and 6–11) that favour an even allocation of the budget show almost the same level of robustness. For a tighter restriction of substitutability (larger α in eq. (6)) the even allocation would eventually become most robust.

The model analysis is based on a number of assumptions. One assumption is that the overall budget, available for both time periods and regions, is fixed, so that the portion of the budget not spent in the first period is completely available with certainty in the second period. Given that the second period may be decades after the first, this assumption appears to be quite strong, if not unrealistic. Therefore the model results should not be interpreted in a literal manner but more general in the sense that they tell under which circumstances conservation action should be favoured in the present and when it may be sensible to postpone some decisions or conservation actions into the future while using present scarce funds for saving, investments or other political goals. While a conservation organisation or agency may not be equipped with such a high level freedom and certainty about future funding, a society as a whole is able to implement such policies. An example for this is the Norwegian Government Pension Fund that invests present revenues from the country's oil and gas resources to ensure society's long term wealth (https://www.nbim.no/).

Another important assumption is the neglection of spatial and temporal interactions. Under spatial interactions the ecological benefit in region 1 could affect the ecological benefit in region 2 and vice versa. Such interactions have been considered, e.g., by Wu and Boggess (1999) and Wätzold and Drechsler (2005). A biological motivation of spatial interactions is the ecological metapopulation concept (Hanski 1999) which considers that local populations on individual habitat patches interact through the dispersal of individuals, so habitat patches that have become empty due to the extinction of the local population can be colonised by other local populations. The two studies of Wu and Boggess (1999) and Wätzold and Drechsler (2005) indicate that spatial interactions call for a more even allocation of conservation budgets, as it has been obtained in the present study for the cases of concave benefit functions ($z = 0.5$) and increasing marginal costs ($e = 0.05$).

Temporal interactions include, e.g., the influence of the ecological benefit in period 1 on the ecological benefit in period 2. Managing a species population in a good state in period 1 (measured by a high ecological benefit in that period) increases the likelihood of that species being in a good state in period 2. Conversely, if no area is conserved in period 1 so the species goes extinct before period 2, it will not recover by any conservation effort in period 2 (unless individuals from other local populations immigrate) and the ecological benefit in period 2 will always be zero. This is an example of path dependence (Liebowitz and Margolis 1995, Drechsler and Wätzold 2020) where an action in the past affects the present set of possible actions and the effects of these actions. In this manner, the decision in the first period is to some extent irreversible. Irreversibility is a major problem in dynamic decision making (e.g., Arrow and Fisher (1974), Albers (1996), Lewis and Polasky (2018)). Preliminary analyses of a variant of the present model that includes the described path dependence led to expected results: that the cost-effective budget share in period 1 increased compared to the case without temporal interaction because higher period-1 benefits allowed for higher period-2 benefits, while the share in period 2 decreased because the period-2 benefits had no influence on the period-1 benefits.

In that manner, the consideration of path dependence would even strengthen the above-mentioned result that the most robust strategy is to concentrate the budget in the first time period. This would, however, imply that high benefits are obtained only in the first period while benefits in the second time period are small or even zero (an allocation that is even more favoured under risk aversion, as argued above). A more constant temporal flow of ecological benefits is obtained if substitution between the benefits of the two time periods is restricted and a more even temporal allocation of the budget is cost-effective. Altogether, the two arguments of path dependence and a constant flow of benefits seem to have opposite implications, which calls for future research on this issue.

Future research might further consider models with three or more regions that interact through dispersal of individuals, and include temporal interactions, e.g., through the explicit consideration of species population dynamics. This would also move the rather abstract present analysis closer to real-world application.

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