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Use of many low-level conservation targets reduces high-level conservation performance

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A B S T R A C T

The prevalent approach for reserve network design is within the framework of systematic conservation planning which includes target setting as an integral step. In target-based planning the conservation goal is translated into conservation targets for biodiversity features, such as species, habitats or ecosystem services. In effect, many targets are set for factors that can be considered as low-level components of biodiversity as a whole. This paper investigates the relations between common formulations for reserve selection, including minimum set cover, maximum coverage and maximal utility planning. We conclusively show how the use of many low-level targets can significantly reduce return on conservation investment. This finding should influence the way targets are viewed in systematic conservation planning, and it is directly relevant for globally accepted state-of-the-art conservation practices. We also describe a novel planning framework combining target- and benefit-based approaches which could be widely useful in the design of conservation area networks.

1. Introduction

Systematic conservation planning (Margules and Pressey, 2000; Margules and Sarkar, 2007) and spatial conservation prioritization (Moilanen et al., 2009c) are disciplines of conservation biology that focus on spatial conservation planning, using methods frequently called reserve selection or site selection algorithms. One of the integral steps of systematic conservation planning is the translation of conservation goals, concerning representativeness and persistence of biodiversity, into specific targets that are given individually for biodiversity features, such as species or habitat types (Pressey et al., 2003; Sarkar et al., 2006). Targets are strategic to conservation policy in many countries and their use within the systematic conservation planning framework is internationally recognized as best practice (Carwardine et al., 2009). Also many conservation planning software tools have implemented target-based planning as the primary planning method (Ball and Possingham, 2000; Ciarleglio et al., 2009; Pressey et al., 2009).

On theoretical ground conservation targets should be based on ecological thresholds related to extinction probabilities of species or efficiency of ecosystem functions (Tear et al., 2005; Rondinini and Chiozza, 2010). It has been argued that in practice targets may be set arbitrarily, without ecological relevance (Rodrigues and Gaston, 2001; Solomon et al., 2003; Svancara et al., 2005; Wiersma and Nudds, 2006). It is ultimately the spatial population dynamics and the spatially structured landscape which determine the distribution and abundance of species as well as their regional persistence (Cabeza and Moilanen, 2001). Because targets are in principle developed independently for biodiversity features, the spatial nestedness hierarchy of species distributions (Tilman, 1994) and the interaction of these distributions with land cost cannot be completely accounted for in target setting. Consequently, conservation resources may be spent on individual features that occur in otherwise feature-poor or expensive areas leading to a reduced overall return on conservation investment (Moilanen and Arponen, 2011; Di Minin and Moilanen, 2012).

This study investigates the fundamentals of the target-based model of spatial conservation planning. We concentrate on the question of how setting of low-level targets affects the high-level conservation performance. By low-level targets we refer to targets for individual biodiversity features such as representation levels of species, minimum population counts, connectivity distance thresholds and other similar quantities, which can be given for a large number of species or habitats and which all are components of biodiversity as a whole. In contrast, high-level targets are targets for measures of aggregate conservation objectives such as average representation of species. They also include large-scale goals such as 'prevent extinctions of species' or 'increase the coverage of terrestrial conservation areas to 17%' (Normile, 2010).

The analysis will be done by exploring the relations between common cost-efficient mathematical formulations for reserve

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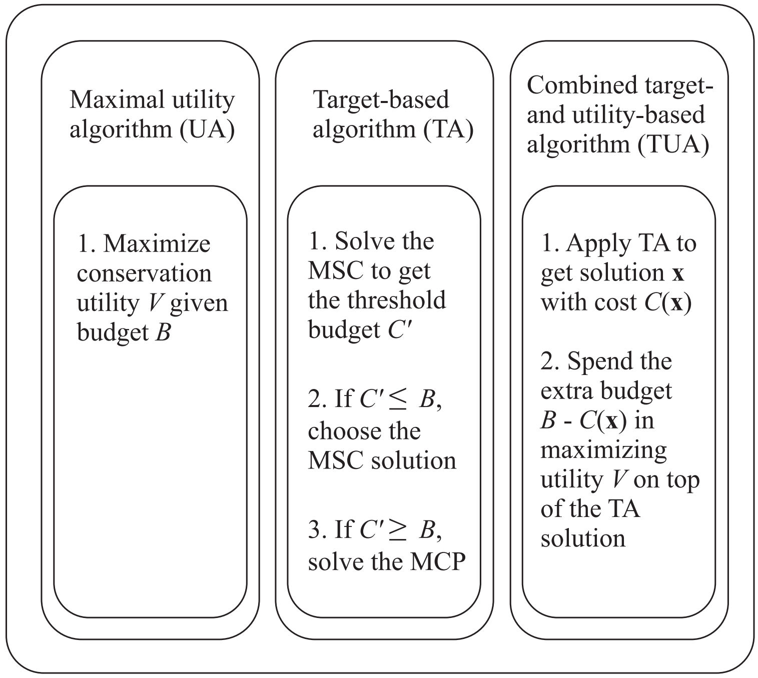

Fig. 1. Summary of reserve selection algorithms analyzed.

selection, including minimum set cover, maximum coverage and maximal utility planning (Moilanen et al., 2009b). Minimum set cover problem has the objective of finding a solution which achieves all given (low-level) conservation targets at minimum cost (Pressey and Tully, 1994; Haight et al., 2000; ReVelle et al., 2002). Maximum coverage problem has the objective of satisfying as many targets as possible under limited resources (Camm et al., 1996; Csuti et al., 1997; Pressey et al., 1997; Arthur et al., 2002). Maximal utility planning is a generalization of maximum coverage planning where the aim is to maximize a given conservation value function. A simple variant of utility maximization assumes that the conservation value for each feature is a continuously increasing function of the level of representation of that feature and the total high-level conservation value is an additive sum across features (Hof and Raphael, 1993; Bevers et al., 1995; Arponen et al., 2005). In cost-efficient planning a useful measure is return on investment (ROI), which measures the conservation utility achieved per cost of the conservation action (Murdoch et al., 2007; Underwood et al., 2008; Evans et al., 2011).

We develop relevant performance measures for comparing different planning frameworks. Using a relative return on investment measure we show how the use of low-level targets can lead to significant reduction in high-level performance – a general fact which has recently been suggested based on logical and empirical arguments (Moilanen and Arponen, 2011; Di Minin and Moilanen, 2012). We show that if a high-level aggregate measure of conservation value is given, then setting low-level targets to the component variables (biodiversity features) of the high-level measure always leads to reduced conservation performance. This finding should influence the way targets are viewed in systematic conservation planning, which is a moderately large and policy-relevant sub-field of conservation science: a limited Web-of-Science search ("systematic conservation planning" OR "reserve selection") on 10th of May 2012 found 786 publications, mostly from the past decade, which received 3500 citations in 2011. In addition to quantifying conservation performance, we discuss a novel planning framework that combines target- and benefit-based approaches in a manner that benefits from the advantages of both and which could therefore be widely useful in the design of conservation area networks.

2. Methods

We start by presenting the well-known utility-maximizing and target-based planning problems in a unified context as step-by-step planning algorithms. We then introduce a high-level performance measure, which corresponds to relative return on investment, to compare their solutions. Because our focus is on cost-efficiency, the comparison is most natural between solutions that are equally expensive. This is not necessarily the case for solutions of classical maximal utility or target-based frameworks. For this reason we introduce a novel combined planning algorithm, where any resources which remain after a target-based planning problem has been solved are spent on maximizing conservation value on top of the target-based solution (see Fig. 1 for a summary of reserve selection algorithms analyzed). Aside from being useful in the present analysis, this new framework could be widely useful as a novel target-based strategy for the design of conservation area networks. We also discuss variants of this combined target- and utility-based framework.

2.1. Maximal utility reserve selection and return on investment

Let $V(\mathbf{x})$ denote the conservation value of a reserve network $\mathbf{x}$. Suppose that the resources invested in the network have a cost $C(\mathbf{x})$ which is bounded above by a given budget B. The basic problem of selecting the reserve network which maximizes the conservation value is then (Hof and Raphael, 1993; Bevers et al., 1995; Arponen et al., 2005):

$$\begin{aligned} &\max_{\mathbf{x} \in E} V(\mathbf{x}) \\ &\text{s.t.} \quad C(\mathbf{x}) \leq B. \end{aligned} \tag{1}$$

Here a network $\mathbf{x} = (x_1, \ldots x_m)$ consists of m sites, where x_i is the selected fraction of site i (see Table 1 for the notation). Classically, x_i is either 0 or 1, indicating that a site is either selected or not. We will assume that x_i is a continuous variable, which can take any value between 0 and 1. In this case x_i can be interpreted as a fraction of the area of the site or as some conservation action (e.g. habitat restoration or maintenance) applied to the site (Moilanen et al.,

Table 1
Mathematical symbols.

Symbol	Explanation
n	Number of features
m	Number of sites available
$\mathbf{x} = (x_1, \ldots, x_m)$	Selected reserve network, where $x_i \in [0, 1]$ denotes the selected fraction of site i
$E = [0, 1]^m$	Set of all possible networks, i.e. vectors $\mathbf{x} = (x_1, \ldots, x_m)$ for which $0 \le x_i \le 1$
V	Conservation value of the network
C	Conservation cost of the network; $C(\mathbf{x}) = \mathbf{c} \cdot \mathbf{x}$
$c = (c_1, \ldots, c_m)$	Cost vector, where $c_i \ge 0$ is the cost of reserve i. The cost of adding fraction x_i of reserve i to the network is assumed to be linear: $c_i x_i$
B	Total conservation budget
$R_j(\mathbf{x}) = \mathbf{r}_j \cdot \mathbf{x}$	Representation of feature j in the network $\mathbf{x}$. Here $\mathbf{r}_j = (r_{1i}, \ldots r_{mi})$, where $r_{ji} \in [0, 1]$ is the representation of feature j in the site i
$V_j(R_j(\mathbf{x}))$	Value of the representation of feature j in the network $\mathbf{x}$
T_j	Target for the representation of feature j, $T_j \in [0, 1]$
$\chi_{\{R_j \ge T_j\}}(\mathbf{x})$	Indicator function taking value 1 when $R_j(\mathbf{x}) \ge T_j$, i.e. when target T_j is met, and zero otherwise

2009b). The arguments presented in this paper can be formulated in both discrete and continuous case, but in our analysis the latter case has the advantage that there always exists a reserve selection whose cost equals the budget. Note that in general solutions to reserve selection algorithms such as (1) are not necessarily unique. Because the focus here is on cost-efficiency, we will always pick from the non-unique solutions a least expensive one.

Value functions V are sometimes called utility or benefit functions in the literature. Hence a reserve selection strategy based on solving problem (1) will be called maximal utility algorithm, henceforth abbreviated as UA. It is also naturally linked to return on conservation investment (ROI) analysis (Murdoch et al., 2007; Underwood et al., 2008; Evans et al., 2011). Indeed, given a budget level B, for an optimal solution $\mathbf{x}'$ to (1), maximal return on investment is given by $V(\mathbf{x}')$. Hence, for fixed investment levels, the optimal conservation utility and return on investment are comparable quantities. We make the natural assumptions that V is (i) nonnegative and (ii) monotonic (i.e. nondecreasing in each x_i), so that adding any site (or any feature) to a solution does not decrease the total value. Although the general arguments in this paper do not depend on the particular definition of V, it is convenient to fix a formulation: following Arponen et al. (2005) we will assume that the value of a reserve network is the sum of over the values of representations of individual species (or other biodiversity features, such as environment types or ecosystem services):

$$V(\mathbf{x}) = \sum_{j=1}^{n} V_j(R_j(\mathbf{x})), \tag{2}$$

where $R_j(\mathbf{x})$ is the representation of species j and $V_j(R_j(\mathbf{x}))$ is its value in the network $\mathbf{x}$. For example, motivated by the species-area relationship, the value of the representation of a species can be modelled by a function of the form $V_j(R_j) = w_j R_j^{zj}$, where w_j is a positive weight and the exponent z_j takes a value between zero and one (Fig. 2a). We will restrict ourselves to the unweighted case $w_j = 1$ for simplicity. With the choice $z_j = 1$ for all species the function (2) becomes linear and thus equals the total representation across all species. We will also consider the case where $0 < z_j < 1$ in which the utility function is strictly concave and ensures that it is beneficial to include all species in the optimal solution. We will further assume for simplicity that the cost is given by a linear function; $C(\mathbf{x}) = \sum_{i=1}^{m} c_i x_i$. These parameter choices are made for convenience; it is clear that the subsequent analysis holds for a much larger class of utility functions and constraints.

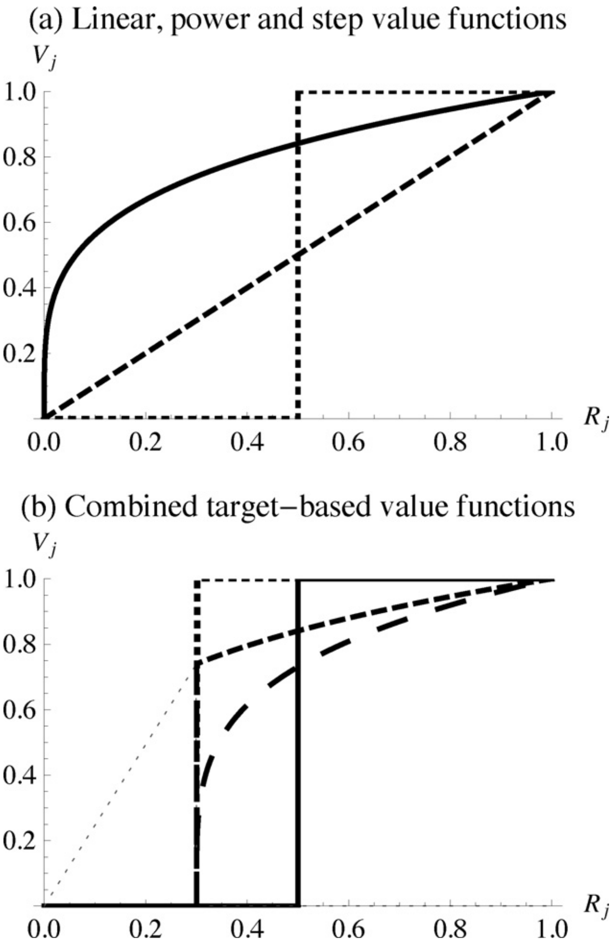

Fig. 2. Alternative utility functions V_j for the representation R_j of a species in utility-based and combined target-based modelling. (a) Utility- and target-based modelling: power function (solid), linear function (dashed) and a step function corresponding to a target of 0.5 (dotted). (b) Target-based and combined modelling: step functions corresponding to the original target (solid) and a reduced target (dotted), a combined step and utility function (short dashing), a Zonation-type translated value function (long dashing; Moilanen, 2007), and a modification of combined step and utility function which values fractional target achievement (thin dotted line).

2.2. Classical target-based reserve selection algorithm

Setting targets for a set of biodiversity features is an integral part of the systematic conservation planning framework (Margules and Sarkar, 2007; Carwardine et al., 2009). Two common target-based approaches are the minimum set cover (MSC) and maximum coverage problems (MCP) (Camm et al., 1996; ReVelle et al., 2002). In MSC the aim is to achieve the given targets with least cost. Hence, in MSC it is *a priori* assumed, or known, that funding will be sufficient for covering all targets. In MCP the aim is to maximize the number of targets met given insufficient resources. Keeping other parameters constant, MSC and MCP thus apply to different situations depending on the size of the budget. Based on this observation, given a budget B, the classical target-based planning algorithm (TA) can be reformulated as a combination of both MSC and MCP in the following three steps:

Step 1: Calculate the threshold budget C' by solving the MSC:

$$C' = \min_{\mathbf{x} \in E} C(\mathbf{x})$$
$$\text{s.t.} \quad R_j(\mathbf{x}) \ge T_j, \quad j = 1, \ldots, n.$$

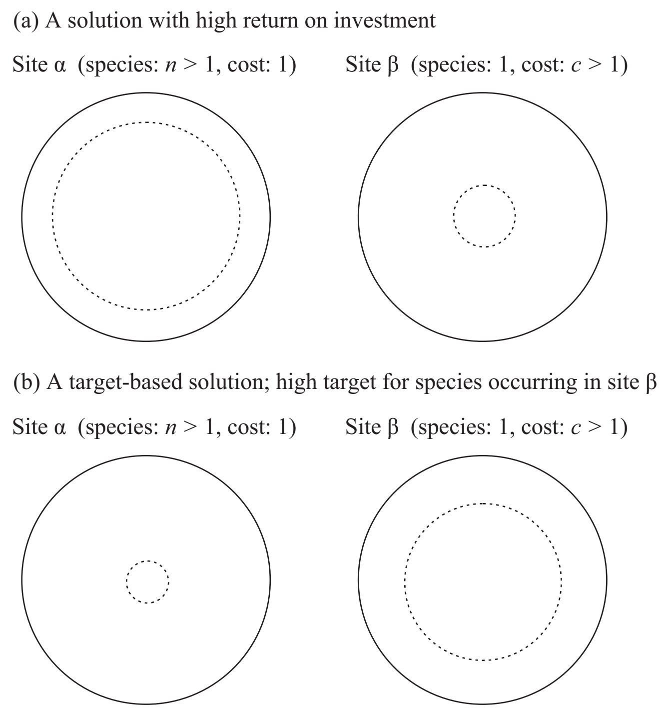

Fig. 3. An example of how targets may reduce return on conservation investment when features and land cost are unevenly distributed. (a) A solution yielding high ROI calculated in terms of average representation of species (dashed circles). Most of site α is protected because of higher ROI obtained. (b) A solution from a target-based model where the single species occurring in site β has been given a high target. Most of the resources are spent to meet the target. The total protected area is smaller than in solution (a) because of the higher land cost of site β. The many species in site α lose protection because the resources are consumed by the single species in site β.

Step 2: If $C' \leq B$, that is, the budget is sufficient for covering all targets (or, if no budget is given in advance), then the above solution is selected.
Step 3: If $B < C'$, then the budget is insufficient and a solution of the following MCP is selected: Solve problem (1) using the step utility function:

$$\max_{\mathbf{x} \in E} \sum_{j=1}^{n} \chi_{\{R_j \geq T_j\}}(\mathbf{x}).$$

Characteristics of target-based planning have been extensively reviewed in the literature (see, for example, Carwardine et al., 2009; Moilanen and Arponen, 2011). We next briefly point out some of its properties which motivate the introduction of the combined target- and utility-based model below. First, if a conservation budget is given, then the TA framework as presented above does not necessarily spend this budget entirely, because the cost of optimal solutions of both MSC and MCP usually stay strictly below the given budget. Second, target-setting may lead to unbalanced allocation of resources between reserves because low-level targets may be set independently for features ignoring the nestedness structure of species distributions (Moilanen and Arponen, 2011; Di Minin and Moilanen, 2012) (see Fig. 3 for an example). Third, the MCP can have many (nearly) optimal solutions that yield very different return in terms of feature representation. To illustrate this fact, suppose that there are two reserves α and β with the associated pair of actions $\mathbf{x} = (x_\alpha, x_\beta)$ and that there are two species with representation levels $r_{i\alpha} = r_{2\beta} = 1, \quad r_{1\beta} = r_{2\alpha} = 0$. The respective marginal costs are $c_\alpha = c_\beta = 1$ and we are given a budget $B = 1$. Then, given targets $T_1 = 1 - \varepsilon$ and $T_2 = 1 + \varepsilon$, the optimal MCP solution is (1,0) for $\varepsilon > 0$, (0,1) for $\varepsilon < 0$. In other words, for $\varepsilon \neq 0$, the budget only suffices for satisfying one of the targets, and a small change causes a discontinuous jump from favouring one site to favouring the other, potentially leading to a completely different set of protected species.

2.3. A combined target- and utility-based framework

The maximal utility and target-based algorithms are fundamentally different in their treatment of resources: in the usual case where the utility function is strictly monotonic (i.e. increasing as a function of biodiversity features) the given budget is spent entirely in UA whereas in TA this may not be the case. This difference in resources spent is likely to affect the conservation outcome of the solutions. We next introduce a generalized framework, combined target- and utility-based algorithm (TUA), which combines both frameworks UA and TA in a cost-efficient manner. In TUA the planner's aim is to first account for the targets by solving an MSC or MCP and as a second step to spend the remaining part of the budget in maximizing conservation utility on top of the target-based solution. Based on the TA algorithm above, TUA can be formulated in the following three steps:

Step 1: Calculate the threshold budget C' by solving the MSC (TA, Step 1).
Step 2: If $C' \leq B$, then the budget is sufficient for covering all targets. Spend the budget up to C' as in solution to the MSC and the remaining part $B - C'$ in maximizing utility V. These steps can be conveniently formulated as a single optimization problem: Solve the utility-based problem (1) equipped with the additional target constraint:

$$R_j(\mathbf{x}) \geq T_j \quad \text{for all} \quad j = 1, \ldots n. \tag{3}$$

Step 3: If $B < C'$, then the budget is insufficient. Solve first the MCP (TA, Step 3) and denote its solution by $\mathbf{x}'$. Note that because the MCP utility function is not strictly monotonic, it is possible that $C(\mathbf{x}') < B$. Spend the remaining part of the resources $B - C(\mathbf{x}')$ in maximizing utility V, by solving problem (1) equipped with the additional constraint:

$$x_i \geq x_i' \quad \text{for all} \quad i = 1, \ldots m. \tag{4}$$

This framework extends both utility-maximizing and target-based frameworks: if no targets are set, then TUA is simply a maximal utility algorithm, if $B = C'$, then the generalized algorithm equals solving the SCP, and for suitable values $B < C'$ the TUA equals solving an MCP.

2.4. Measure of conservation performance

Given any value function V, cost C, targets T and budget B, let $\mathbf{x}'_{\mathrm{U}}, \mathbf{x}'_{\mathrm{T}}$ and $\mathbf{x}'_{\mathrm{TU}}$ denote optimal solutions given by the algorithms UA, TA and TUA, respectively. Then the chain of inequalities always holds:

$$V(\mathbf{x}'_{\mathrm{U}}) \geq V(x'_{\mathrm{TU}}) \geq V(\mathbf{x}'_{\mathrm{T}}). \tag{5}$$

Moreover, the inequalities are strict for common parameter choices, which would correspond to typical biological data in which there are major differences between locations in both species composition and land price. In other words, the general utility-maximizing algorithm yields in general a higher conservation value than the combined target- and utility-based algorithm, which in turn yields more value than the solutions to the basic target-based algorithm. The left-hand inequality in (5) follows because any admissible solutions to problems (3) and (4) are admissible also to problem (1), where no target constraints are present. Hence in UA conservation value is maximized over a larger set of possible reserve selections than in TUA and the maximum value from the former is at least as large as from the latter. The extent to which this reduction happens depends on the size and distribution of targets: either the constraints are strictly binding in which case the inequality is strict, or they are not in which case targets are redundant in the model. This can be interpreted so that any resources allocated to meet (expensive) targets (for rare features) diminish resources that could increase conservation value in more cost-efficient locations. The right-hand inequality follows by construction of the TUA, which cost-efficiently spends resources $B - C(\mathbf{x}'_{\mathrm{T}})$ on increasing conservation value. Because in TU for most choices of B we have $C(\mathbf{x}'_{\mathrm{T}}) < B$, this inequality is in general strict. It may be of interest to note that from UA one can calculate back the optimal utility-based targets T'_j, i.e. the targets for which TUA provides the same solution. One can further check that $T'_j \le T_j$ for all targets T_j which are strictly binding. This gives an alternative way to view (5).

Motivated by (5) we will measure the high-level conservation performance of any solution $\mathbf{x}$ by a relative utility measure given by:

$$E(\mathbf{x}) = \frac{V(\mathbf{x})}{V(\mathbf{x}'_{\mathrm{U}})}.$$

As the main performance measure for targets we use $M_{\mathrm{TU}} = E(\mathbf{x}'_{\mathrm{TU}})$, which equals the relative return on investment returned by the combined algorithm. If M_{TU} equals one, then target setting has no effect on conservation value (because targets are small or budget is large), otherwise $M_{\mathrm{TU}} < 1$. We will also analyze the measure $M_{\mathrm{T}} = E(\mathbf{x}'_{\mathrm{T}})$ based on the TA framework, although it is less neutral because of the possibly smaller amount of resources spent in the TA framework compared to UA. The quantity M_{TU} can alternatively be interpreted as a measure of biological replacement cost (difference between unconstrained solution and solution following imposition of additional constraints) of targets (Cabeza and Moilanen, 2006; Moilanen et al., 2009a; Moilanen and Arponen, 2011). In fact, for any solution $\mathbf{x}$, the ratio $E(\mathbf{x})$ measures the cost of replacing $\mathbf{x}'_{\mathrm{U}}$ by $\mathbf{x}$ and hence generalizes the concept of replacement cost to an arbitrary feasible solution of problem (1).

2.5. Further techniques for combining targets and utility functions

We will next point out some modifications of TUA, which might be useful in applications, as well as some alternative techniques for combining targets and maximal utility planning. Because in TUA a given budget is spent entirely regardless of the target levels, the framework is not as sensitive to readjustment of the targets as TA. For example, to ensure some level of conservation performance or partial target coverage, the planner might want to reduce some or all of the targets by a certain percentage (cf. Fig. 2b) and distribute the remaining resources to maximize utility. In the case where the budget is not sufficient for covering all targets, this could be done by replacing Step 3 of TUA by:

Step 3′: If $B < C'$, reduce targets T_j and go back to Step 1. In other words, calculate a new (lower) threshold budget C' using the reduced targets and repeat until $C' \le B$.

In common applications of MSC the budget is not known in advance but rather becomes defined by the cost of the minimum set solution ($B = C'$). Also in this case it is possible to apply a similar strategy by reducing the target levels, recalculating the threshold budget and spending the released resources in maximizing conservation utility on top of the reduced MSC solution.

A different type of approach for combining classical target- and utility-based planning is obtained by considering a maximal utility problem with additive utility functions (2), where $V_j(R_j)$ is replaced by the step-type function $V_j(R_j) \times \chi_{\{R_j \ge T_j\}}$, where the utility is positive only after the target has been attained (see Fig. 2b). In fact, the utility function maximized in step 2 of TUA is interchangeable with a function of this form. In contrast to TUA, in this approach the partial achievement of a target is not rewarded. An alternative way of rewarding partial achievement is to add a linear element in the step function which increases the utility until target level is attained (Moilanen, 2007) (also see Fig. 2b). A further variant of the above approach based on a translated utility function $V_j(R_j - T_j) \times \chi_{\{R_j \ge T_j\}}$ is available in the Zonation software (Moilanen, 2007). The multitude of options at hand shows that there are several natural ways of incorporating targets in conservation decision making and that it is important to be aware of the differences of such techniques. As MCP, the strategies described above are special cases of the maximal utility problem (1), which in a general form can be based on any method for aggregating conservation value, including process-based models with dynamic feedbacks. While our conclusions hold for very general utility-based models, a detailed analysis of such options goes out of the scope of this paper.

3. Results

Our main results concern conservation performance of low-level targets. The first result, implied by inequality (5) above, states that when comparing classical target- and utility-based planning algorithms in terms of the conservation performance measures M_{TU} and M_{T}, the performance of target-based algorithms is at most as good as that of the maximal utility algorithm. This qualitative result is general, but it does not include information on how much performance can be reduced. We next quantify the performance gap by considering specific examples. In particular, the next example shows that when the model parameters are asymmetric (species occurrence density, land cost or targets vary across the data), which is the usual case in real world problems, the performance of target-based models is often strictly and considerably smaller than that of maximal utility models. In other words, for suitable parameters, the gap between the quantities in (5) can be arbitrarily large in the presence of inefficient targets.

Consider a simple setting of two candidate areas α and β, and that a fraction between zero and one can be chosen for protection from each (cf. Fig. 3). Suppose that the areas have marginal costs c_α and c_β, respectively, with $1 = c_\alpha \le c_\beta = c$. Suppose there are $n+1$ species, of which one occurs in site β only and n occur in site α only. This corresponds to the common real-world situation that site β is of a relatively species-poor habitat type and site α of a species-rich habitat type, each with their own species assemblage. Consider a high-level conservation utility function as in (2) with $V_j(R_j(\mathbf{x})) = R_j(\mathbf{x})^z$ so that $V(\mathbf{x}) = nx_\alpha^z + x_\beta^z$; if $z < 1$, this formulation can be interpreted as minimization of extinction rates via the species-area relationship. As before, the budget is denoted by B and we are given targets T_α for the representation levels of all species occurring in area α and a target T_β for the species occurring in area β. This setting essentially captures all relevant parameter combinations in a two-reserve model except for the cases where the species overlap. The purpose is to conclusively show that the performance of targets can be poor when sites are unbalanced in terms of species richness, per-area cost or target levels.

Table 2 collects results from five selected scenarios of the above example as functions of targets using both a linear and strictly concave (power) functions for conservation value. In each scenario the performance measure M_{TU} takes values between zero and one depending on the levels targets. The corresponding TA solution M_{T} is presented for comparison. The scenarios in Table 2 are not comprehensive. In fact, the parameters are chosen so that in each case the cost of achieving targets is below or equal to the budget, $C(\mathbf{x}'_{\mathrm{T}}) \le B$, so that in both TA and TUA the primary target-based

Table 2
Performance of targets in selected scenarios in a two-reserve model. The default assumptions for each scenario are $n = 1,\quad c_\alpha = c_\beta = 1,\quad T_\alpha = T_\beta = T \leq 1/2$ and $B = 1$ (if not otherwise indicated).

Scenario	Linear V ($z = 1$)		Strictly concave V ($0 < z < 1$)	
	M_{TU}	M_T	M_{TU}	M_T
(i) Balanced	1	$2T$	1	$\frac{2T^z}{2^{1-z}}$
(ii) Unbalanced species count ($n \geq ((1-T)/T)^{1-z}$)	$1 - T\frac{n-1}{n}$	$T\frac{n+1}{n}$	$\frac{n(1-T)^z+T^z}{(n^{1/(1-z)}+1)^{1-z}}$	$\frac{T^z(n+1)}{(n^{1/(1-z)}+1)^{1-z}}$
(iii) Unbalanced marginal costs ($C_\beta = c \geq 1,\quad 1 \leq 1/T - c \leq c^{1/(1-z)}$)	$1-(1-c)T$	$2T$	$\frac{c(T^z+(1-cT)^z)}{(c^{1/(1-z)}+c)^{1-z}}$	$\frac{2cT^z}{(c^{1/(1-z)}+c)^{1-z}}$
(iv) Unbalanced targets ($T_\alpha = 0,\quad T_\beta = T \leq 1$)	1	T	$\frac{(1-T)^z+T^z}{2^{1-z}}$	$\frac{T^z}{2^{1-z}}$
(v) Unbalanced species count and targets ($T_\alpha = 0,\quad T_\beta = T \leq 1,\quad n \geq ((1-T)/T)^{1-z}$)	$1 - T\frac{n-1}{n}$	$\frac{T}{n}$	$\frac{n(1-T)^z+T^z}{(n^{1/(1-z)}+1)^{1-z}}$	$\frac{T^z}{(n^{1/(1-z)}+1)^{1-z}}$

model solved is minimum set coverage, corresponding also to the case of purposefully reduced targets (Step 3′ of the modified TUA). If the species count or marginal costs are unbalanced between the sites (cases (ii) and (iii)), the performance of target-based models is reduced. The effect on performance is most extreme when more than one parameter is unbalanced: in the case of unbalanced species count and targets (case (v)), the performance M_{TU} tends to zero as the target T_β approaches one and the species count on α approaches infinity. Cases (iii) and (v) from Table 2 have further been plotted in Fig. 4 for the linear value function ($z = 1$), measuring the fraction of species distributions protected. It can be seen that in both cases conservation performance measures M_{TU} and M_T decrease as asymmetry in model parameters increases (along y-axis) and that the performance is always higher for the combined

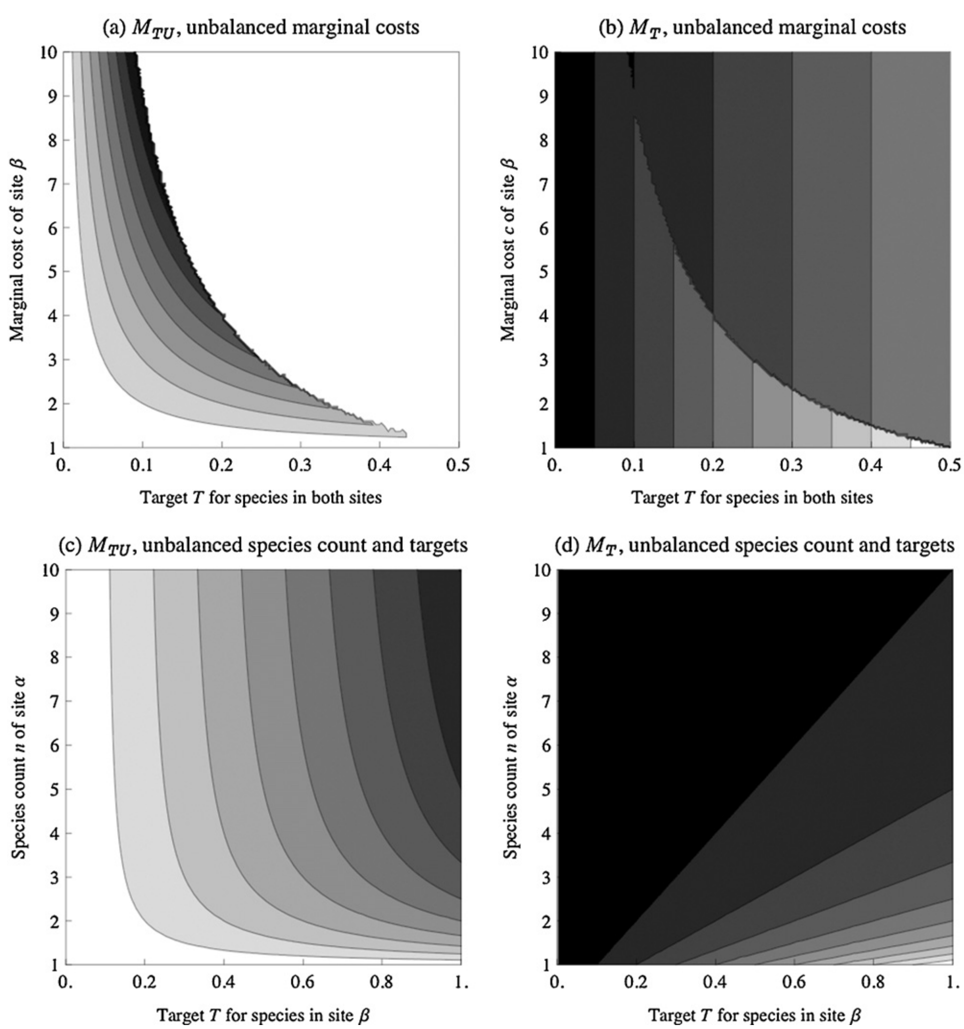

Fig. 4. Conservation performance of target-based models as a function of targets and the land cost of site β (panels (a) and (b)) or species count of site α (panels (c) and (d)) assuming the budget $B = 1$. Panels (a) and (c) show the value of the measure M_{TU}. Black colour corresponds to zero performance and white colour corresponds to best performance ($M_{TU} = 1$). Panels (b) and (d) give the corresponding values for M_T. In all cases conservation performance decreases as asymmetry increases (along y-axis). The TUA framework always performs better than TA. The curve $T(1 + c) = 1$ divides panels (a) and (b) into two parts: in the left-hand side the budget suffices for achieving all targets (MSC), in the right-hand side it does not (MCP).

TUA model (left-hand panels) than for the classical target-based model TA (right-hand panels). In the case of unbalanced marginal costs (panels (a) and (b)), the graph $T(1+c)=1$ divides the plot into two parts with slightly different behaviour: in the left-hand side, where all targets are low, the budget is enough for achieving all targets (TA equals MSC); in the right-hand side, where targets are high, it is not (TA equals MCP). In the latter case the budget only suffices for achieving the targets for species in the less expensive site α. This coincides with maximal utility and hence in the right-hand side the combined model (panel (a)) coincides with the maximal utility model. Hence in this case no performance loss occurs. In the case of unbalanced species count and targets (panels (c) and (d)) the budget is in this example always enough for covering all targets and hence MSC is primarily solved in both TA and TUA.

It is worth stressing that large performance gaps are associated with large asymmetries between model parameters (feature count, marginal costs or targets). In cases where all parameters are symmetric between (two) sites, the differences in the performance of different model frameworks are small or disappear completely. However, in practice conservation planning has to be done in heterogeneous landscapes. The examples above show that in the presence of heterogeneity high-level conservation efficiency can be compromised when independent targets are set for many low-level components of conservation value, such as species.

4. Discussion

The present results conclusively show that conservation models based on the setting of many low-level targets can reduce aggregate high-level conservation performance, measured via return on conservation investment (Murdoch et al., 2007; Underwood et al., 2008; Evans et al., 2011). This behaviour is most pronounced when high targets are given to features that occur in expensive areas and areas with relatively low representation for other features (Fig. 3). Such unbalanced target-setting is most likely to happen when the landscape is heterogeneous in terms of feature occurrence and land cost – a situation which occurs in almost any real-world setting. If all species and land cost are relatively evenly distributed then the performance loss is smaller (row (i) of Table 2) but also the problem of reserve selection is easier (if all sites are identical then their order is not important).

A fundamental source of inefficiency is the practice that targets should be developed independently for features, based on the principles of persistence and adequacy (Margules and Pressey, 2000; Margules and Sarkar, 2007). Independent determination of low-level targets does not account for the fact that species tend to overlap with each other to a variable degree (Figs. 3 and 4c and row (ii) of Table 2). When this nestedness of species distributions is not accounted for in target setting, high targets may be given for isolated species in expensive areas which again may reduce the total return on investment. On the other hand, for overlapping species some targets may be unnecessary because protecting an area may simultaneously cover (and exceed) several targets. Then again, completely accounting for the nestedness of features would shift target-based planning towards utility-based planning, as targets would be calculated from an effectively utility-based model. At the practical level, accounting for species overlap in target setting would be very arduous because of the high number of pairs of features that would need to be examined. Even in a country with a modest 10,000 species, there are 50 million potential pairwise overlaps to examine, and a proper analysis would in addition include the multitude of overlapping triplets, quadruples, etc. Then, targets can be given to multiple quantities per species (feature), total representation, population counts, connectivity distances between patches, persistence (Margules and Sarkar, 2007). Furthermore, targets could be given not only to present distributions of features, but also to future expected distributions following climate change (Pearson and Dawson, 2005). It should be apparent that given the multitude of targets that need to be specified, there is great potential for setting targets that greatly reduce return on conservation investment as a whole.

In the language of optimization, the reduced conservation performance results from the additional target constraint in the target-based or combined models compared to the maximal utility model. Although we have considered specific parameters for convenience (such as additive utility functions), it is clear that the conclusion holds for quite general set of utility functions as well as target and budget constraints. If some performance loss occurs, then some target constraints necessarily are strictly binding (and the corresponding feature representation is at the target level). Other targets are not in effect (and hence not necessary) or they are precisely optimal (which happens comparatively rarely if targets are not back-calculated as results of utility-based models).

We suggest that the combined target- and utility-based method (TUA) could be a useful intermediate approach for target-based planning. This method can be viewed as an extension of both target- and utility-based approaches. Given a fixed amount of resources, the method aims to satisfy all targets, but in addition it distributes the remaining resources cost-efficiently ensuring the maximal conservation outcome subject to the target constraints. Because the targets in part drive the model, they can be used for monitoring the conservation outcome as in classical target-based models. Hence this method can be a useful extension of the utility-based method in real-world planning situations also in cases where stakeholders base their negotiations and decisions on targets (Carwardine et al., 2009). The examples above (Table 2 and Fig. 4) show that the TUA framework performs better than the classical target-based models simply because of the cost-effective allocation of all extra resources. Furthermore, we propose that the variant where targets are reduced by a suitable amount in order to save resources for more cost-effective allocation should be a useful modification of the combined approach. Additionally, we point out the existence of publicly available non-target-based spatial conservation prioritization methods (see Moilanen et al., 2011 for references).

5. Conclusions

Target-based spatial prioritization is the norm in systematic conservation planning; in many countries conservation legislation is built around targets, and targets are considered as necessary quantities (Carwardine et al., 2009). Many conservation support tools have implemented target-based planning as the primary planning method (Ball and Possingham, 2000; Ciarleglio et al., 2009; Pressey et al., 2009). We have analyzed mathematically a possible problem with any system that is based on the setting of many low-level targets for many species or other biodiversity features. We have also introduced general frameworks for combining target setting and utility-based planning, which in the past have by-and-large been treated as alternative approaches to spatial conservation planning. In the light of performance, these combined approaches should be useful tools compared to classical target-based models. While the present argument is conceptual and mathematical, it pertains to a practice at the core of systematic conservation planning, which again is a discipline that influences land-use decisions almost at a daily basis around the world (Margules and Sarkar, 2007). Thus, the present results should be carefully considered in light of their impact on conservation planning practices around the world.

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