

Influence of Representation Targets on the Total Area of Conservation-Area Networks

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Abstract: *Systematic conservation planning typically requires specification of quantitative representation targets for biodiversity surrogates such as species, vegetation types, and environmental parameters. Targets are usually specified either as the minimum total area in a conservation-area network in which a surrogate must be present or as the proportion of a surrogate's existing spatial distribution required to be in the network. Because the biological basis for setting targets is often unclear, a better understanding of how targets affect selection of conservation areas is needed. We studied how the total area of conservation-area networks depends on percentage targets ranging from 5% to 95%. We analyzed 12 data sets of different surrogate distributions from 5 regions: Korea, Mexico, Québec, Queensland, and West Virginia. To assess the effect of spatial resolution on the target-area relationship, we also analyzed each data set at 7 spatial resolutions ranging from $0.01^\circ \times 0.01^\circ$ to $0.10^\circ \times 0.10^\circ$. Most of the data sets showed a linear relationship between representation targets and total area of conservation-area networks that was invariant across changes in spatial resolution. The slope of this relationship indicated how total area increased with target level, and our results suggest that greater surrogate representation requires significantly more area. One data set exhibited a highly nonlinear relationship. The results for this data set suggest a new method for setting targets on the basis of the functional form of target-area relationships. In particular, the method shows how the target-area relationship can provide a rationale for setting targets solely on the basis of distributional information about surrogates.*

Keywords: conservation objectives, conservation planning, conservation site prioritization, representation targets, reserve selection, scale analysis, selection of conservation areas

Influencia de los Objetivos de Representación sobre el Área Total de Redes de Áreas de Conservación

Resumen: *La planificación sistemática de la conservación típicamente requiere la especificación de objetivos de representación para sustitutos de la biodiversidad como especies, tipos de vegetación y parámetros ambientales. Los objetivos usualmente son especificados como el área total mínima en una red de áreas de conservación en la que un sustituto debe estar presente o como la proporción de la distribución espacial del sustituto que se requiere en la red. Debido a que la base biológica para definir objetivos a menudo es poco clara, se requiere un mejor entendimiento de cómo afectan los objetivos a la selección de áreas de conservación. Estudiamos cómo el área total de las áreas de conservación depende de objetivos porcentuales que varían entre 5% y 95%. Analizamos 12 conjuntos de datos de distribuciones sustitutas de regiones diferentes: Corea, México, Quebec, Queensland y Virginia del Oeste. Para evaluar el efecto de la resolución espacial sobre la relación objetivo-área también analizamos cada conjunto de datos en 7 resoluciones espaciales entre $0.01^\circ \times 0.01^\circ$ y $0.10^\circ \times 0.10^\circ$. La mayoría de los conjuntos de datos mostraron una relación lineal entre los objetivos de representación y el área total de las redes de áreas de conservación que fue invariable en los cambios de resolución espacial. La pendiente de esta relación indicó cómo aumento el área total con el nivel de representación, y nuestros resultados sugieren que una mayor representación sustituta requiere de más área significativamente. Un conjunto de datos mostró una relación no lineal. Los resultados para este conjunto de datos sugieren un nuevo método para definir objetivos sobre la base de una forma funcional de la relación objetivo-área. En particular, el método muestra que la relación objetivo-área puede proporcionar*

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Paper submitted August 24, 2006; revised manuscript accepted October 1, 2007.

un fundamento para la definición de objetivos con solamente la base de información sobre la distribución de sustitutos.

Palabras Clave: análisis de escala, objetivos de conservación, objetivos de representación, planificación de la conservación, priorización de sitios de conservación, selección de áreas de conservación, selección de reservas

Introduction

Area prioritization algorithms for the selection of conservation-area networks (CANs) are now an indispensable part of systematic conservation planning (Margules & Pressey 2000; Groves et al. 2002; Sarkar et al. 2006; Margules & Sarkar 2007). In addition to addressing socioeconomic concerns and the processes that threaten conservation goals, implementing these algorithms in practical-planning contexts requires specification of quantitative targets (i.e., minimal levels of representation of features of conservation interest, such as species, other taxa, or vegetation types). Targets are typically specified as the total extent (in square kilometers) of surrogates required to be present in a CAN or the proportions of total distributions of surrogates required to be represented. Without explicit, quantitative targets the adequacy of conservation plans cannot be evaluated properly (Pressey et al. 2003).

Ideally, if the second type of target is used, it will reflect the representation levels required to ensure the persistence of surrogates such as species. For some species the choice is fairly clear. To have any chance of persistence, targets of 100% are likely required for highly endangered species, whereas 0% is probably sufficient for widespread, vagile species. For most species that are not at these extremes, however, common methods for assessing persistence have serious shortcomings, especially in guiding conservation planning (Simberloff 1988; Sarkar 2005). The most common method for assessing persistence—population viability analysis—focuses on single species (or occasionally a few species at a time) and rarely considers more than a few factors affecting population decline. As such, it potentially plays a useful role in narrow contexts focused on conserving individual species, but it provides little insight into what targets are needed to conserve multispecies assemblages facing numerous threats (Fieberg & Ellner 2000). The extensive data required to estimate parameters used in these analyses with sufficient precision are also rarely available or obtainable given the temporal and budgetary constraints of practical conservation planning (Ruggiero et al. 1994; Burgman et al. 2001). In a recent review, Tear et al. (2005) argue, “Although viability analyses have occupied research scientists for nearly two decades now, conservation practitioners are still typically at a loss when establishing a quantitative target.”

Without an adequate understanding of what species persistence requires, target choices are typically made

for nonbiological reasons. The widely adopted goal of protecting 10–12% of the total area of nations proposed by several conservation organizations (e.g., WCED 1987; IUCN 1993) has been criticized for being motivated by political expediency rather than ecology (Soulé & Sanjayan 1998). This goal may effectively function as an aspirational benchmark for increasing the area designated for conservation in political contexts, but it is not a representation target, and it is not based on scientific studies of what biodiversity conservation requires. A recent comprehensive review shows that the goal of 10–12% of a nation’s total area falls far short of what conservation planning analyses suggest is required for many regions (Svancara et al. 2005). Results of detailed studies of the Cape Floristic Region of South Africa support a similar conclusion (Pressey et al. 2003; Desmet & Cowling 2004).

Because neither the 10–12% goal nor population viability analyses have provided reliable guidance about what representation targets are required to ensure species persistence, a clear understanding of how targets affect CAN selection is needed. Such an understanding may yield a scientific basis for setting targets, and researchers have begun to address this issue. Pressey and Logan (1998) found that total CAN area for land systems in New South Wales increased with target level and spatial resolution for 2 resolutions and 3 target levels. Warman et al. (2004) analyzed how area size, surrogate type, and target level affected area prioritization for species in the Okanagan region of British Columbia and found results similar to those of Pressey and Logan (1998).

New procedures for setting targets as the proportion of a surrogate’s distribution are also being developed. Burgman et al. (2001) based their method on simple population models for setting targets to ensure the persistence of vascular plants. Their method produces targets of 100, 100, and 54% of the distributions of 3 Queensland plant species. Other researchers found that at least 40–50% of habitats are required to ensure persistence (Fahrig 2001; Flather & Bevers 2002). Pressey et al. (2003) propose several heuristic principles to help set targets for 102 habitat types, 364 plants of the Proteaceae family, and 345 vertebrates in the Cape Floristic Region of South Africa. Results were 10–55% for habitat types, 10–100% for plants, and 10–100% for vertebrates. Desmet and Cowling (2004) set targets with a species-area relationship and found that targets of 14–30% of 42 vegetation types in the Succulent Karoo (South Africa) are required to represent 70–80% of plant species. The

targets established in the last 2 sets of studies are based on explicit considerations of representation alone and are thus lower than those required for biodiversity persistence in the face of fragmentation and other such effects. Nevertheless, even these representation targets are geared implicitly toward ensuring persistence, although they do not explicitly address the ecological processes involved.

Most of these new methods focus on setting targets for specific biodiversity surrogates and require additional data about the demography, abundance, and other vital statistics of these surrogates. These data should be used whenever available, but they often are not, especially when large numbers of surrogates are being considered. We therefore propose a new method, the basis of which is the relationship between uniform targets and total CAN area that does not require such data. This relationship can provide a rationale for setting targets that can complement, and be refined by, other target-setting methods.

Higher targets are beneficial from a conservation standpoint because they select a larger percentage of the distribution of each biodiversity surrogate for inclusion in a CAN. In addition, as the targeted percentage of the distribution of a surrogate increases, there is a concomitant increase in the number of additional biodiversity features that may not have been used as surrogates in the analysis but are conferred protection through protection of the surrogate (Pressey et al. 2003).

Methods

We based our analysis on a target-area function (f), which assigns amounts of land (in square kilometers) to CANs at different target levels, and an area-cost function (g), which assigns costs (in dollars) to amounts of land. The function f is important because it can be directly computed with any area-prioritization algorithm (see below). Thus, if t is the target of representation, then $f(t)$ is the area of the CAN that is needed. Then $g[f(t)]$ is the cost of that area of land. We considered fixed land-acquisition budgets first. Because higher representation targets increase the likelihood of persistence of surrogates, we set targets at the maximum level t^* permitted by the budget (b). To compute t^* , $b = g[f(t^*)]$. This equation allows b to be calculated if t^* is known. Nevertheless, we needed to compute t^* when b is known. We, therefore, solved the inverse of this equation to get the maximum permitted target level, $t^* = f^{-1} [g^{-1} (b)]$.

If b is not fixed and may be increased to achieve higher representations of biodiversity surrogates, the function f can be used to provide a justification for target selection. By showing how the area of nominal CANs increases with the target level, f indicates whether more ambitious targets are worthwhile. Figure 1 shows, schematically, how f can be used for target selection. In particular, if $f = m \cdot t$, where t is the target and m is a constant (i.e., f is a linear function), then the slope m of the line

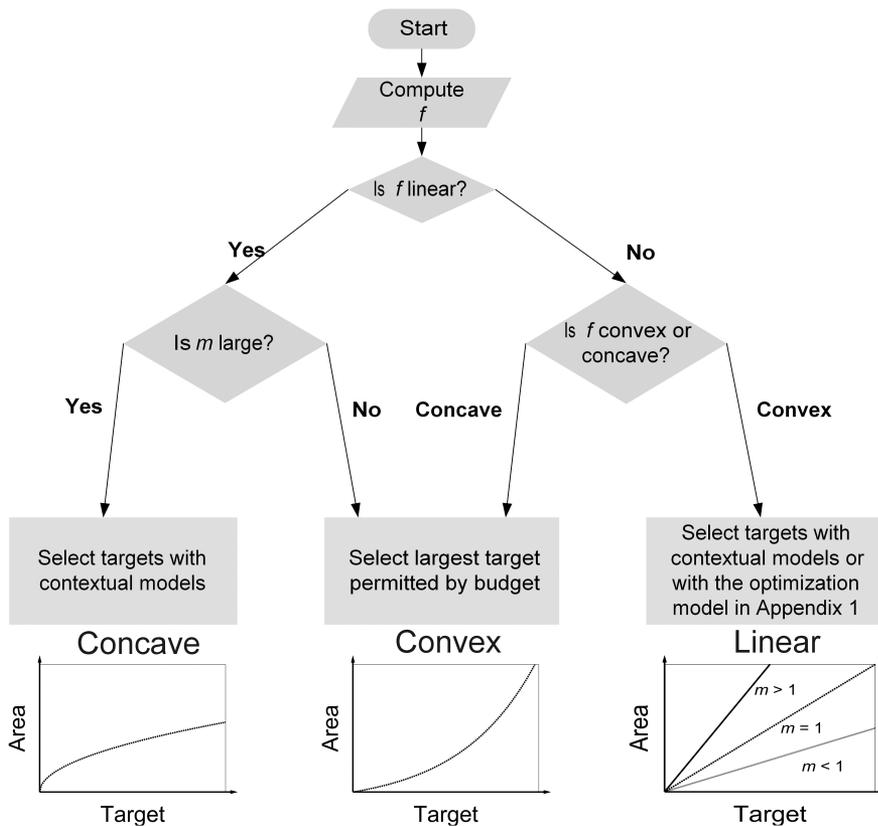


Figure 1. Flowchart of the selection of conservation area targets on the basis of the target-area function (m , is the slope of f , the target-area function). How targets should be selected depends on the functional form of the target-area relationship.

shows how rapidly the area of nominal CANs increases as the representation target levels are increased. When m is small, greater representation of biodiversity surrogates requires relatively small increases in area. This provides a strong basis for selecting higher targets assuming small increases in b are possible. Nevertheless, for $m \gg 1$, greater representation requires significant increases in area. Appropriate targets should then be selected with other context-specific methods. For instance, if environmental surrogates are land-use types, Land-Use Land-Cover (LULC) change models may be used to determine what targets are appropriate (Guhathakurta 2003). If biota (rather than environmental parameters) are being used as surrogates, demographic models (Burgman et al. 2001), species-area curves (Desmet & Cowling 2004), or more general species-heterogeneity approaches (Pressey et al. 2003) are unavoidable. Whether these approaches can be used depends on the data available.

In many circumstances f will not be a linear function. The shape of f can then be used to justify target selection. If f is concave, planners should use the largest target permitted by b because concavity ensures that greater targets require smaller increases in area. If f is convex, one may construct context-specific models if the required data are available. If not, f may be modeled as a sequence of relatively horizontal line segments (e.g., see Fig. 5, which is explained in detail in the Discussion). When f is relatively horizontal, one can increase the target without significantly increasing the area of the CAN (similarly for relatively horizontal portions of a concave target-area function). Our optimization model selected a target associated with relatively horizontal segments of f when the function was convex (see Supplementary Material). The small number of data sets, targets, surrogates, and spatial resolutions analyzed in previous studies prevented systematic determination of f . We computed f for 12 data sets at 7 spatial resolutions and 19 target levels.

Each of the 12 data sets consisted of a set of areas for potential inclusion in a CAN. Surrogates are associated with these areas so that each data set forms a matrix $P = (p_{ij})$ ($i = 1, \dots, n; j = 1, \dots, q$), where $p_{ij} = 1$ if the j th surrogate is found in the i th area; otherwise, $p_{ij} = 0$. The regions we analyzed included the Korean Demilitarized Zone, the Mexican Transvolcanic belt, Oaxaca (Mexico), Québec, Queensland, and West Virginia.

Surrogates for the Korean Demilitarized Zone, Mexican Transvolcanic belt(e), Oaxaca(e), Québec(e), Queensland(e), and West Virginia(e) data sets are distributions of different types of environmental parameters, such as aspect, elevation, mean temperature, minimum temperature, maximum temperature, slope, and soil type (the e index refers to data sets of environmental parameters). Each environmental parameter was partitioned into mutually exclusive classes such that no area contained more than one class. The Mexican Transvolcanic belt(s), Oaxaca(s), and West Virginia(s) data sets were based on

species distributions modeled from the environmental parameter data (the s index refers to data sets of species). The Mexican survey data, Québec(s), and Queensland(s) data sets were derived from biological surveys and museum records of species' distributions. Table 1 and references therein provide details about each data set.

Area prioritization involves solving the following optimization problem: select areas such that the representation target for each biodiversity surrogate is satisfied while minimizing the total size (in square kilometers) of the selected areas. The target area function can be calculated from the results of area prioritization at different target levels. Specifically, the total size of the selected areas is the y -coordinate in plots of the target-area function f . The x -coordinate in these plots is the representation target. We used the ResNet software package for area prioritization (Garson et al. 2002; Sarkar et al. 2002), which implements a heuristic rarity-complementarity algorithm. First, the surrogates were sorted in order of rarity. Next, the area with the rarest surrogate was selected for inclusion in the CAN. Ties were broken by complementarity, that is, by selecting the area with the largest number of surrogates with unsatisfied targets (Sarkar & Margules 2002).

The algorithm was iterated until the targets for all surrogates were satisfied. Because areas selected later in heuristic prioritizations may make previously selected areas redundant, we checked for and removed redundant areas in our final prioritizations (i.e., an area was removed if its removal did not bring a surrogate that had met its target below its target) (see Sarkar et al. 2002 for details). The analysis required 159,600 separate ResNet runs. Because such a large number of area prioritizations cannot be performed with an optimal solver in a reasonable amount of time, we used the fast rarity-complementarity heuristic algorithm of ResNet. Nevertheless, to ensure that results were not artifacts of our algorithms, we used an optimal solver (CPLEX) to solve the hardest problems (species surrogates at finest resolutions for the larger data sets—Mexico, Queensland, Québec, Transvolcanic belt). Optimal solutions were uniformly only marginally better (<1%) than the heuristic solutions (data not shown; but see Fuller et al. 2006).

We used uniform targets of 5–95% at 5% increments for all surrogates. Because the algorithm selected areas by lexical order if no area was uniquely best by rarity or complementarity, we analyzed 100 randomizations of the area order in each data set. Each data point in Figs. 2 through 4 therefore represents the mean of 100 sets of selected areas.

To assess how spatial resolution affected the target-area relationship, each data set was prioritized at 7 spatial resolutions: 0.01° longitude \times 0.01° latitude, $0.02^\circ \times 0.02^\circ$, $0.04^\circ \times 0.04^\circ$, $0.05^\circ \times 0.05^\circ$, $0.06^\circ \times 0.06^\circ$, $0.08^\circ \times 0.08^\circ$, and $0.10^\circ \times 0.10^\circ$. For areas at coarser resolutions,

Table 1. Properties of data sets used in analyses of target–area relationships.

Data set*	Number of areas (mean area size, km ²)								Biodiversity surrogates
	0.01° × 0.01°	0.02° × 0.02°	0.04° × 0.04°	0.05° × 0.05°	0.06° × 0.06°	0.08° × 0.08°	0.10° × 0.10°		
Korean Demilitarized Zone	21,109 (0.972)	5317 (3.89)	1420 (15.6)	925 (24.3)	668 (35.0)	382 (62.2)	238 (97.2)	227 environmental parameters (Hijmans et al. 2005)	
Mexico–survey data	1525 (1.15)	1460 (4.60)	1413 (18.4)	1369 (28.7)	1333 (41.4)	1254 (73.5)	1197 (96.5)	44 mammal species (V. Sánchez-Cordero, personal communication)	
Oaxaca(s)	78,511 (1.18)	19,961 (4.73)	5123 (18.9)	3323 (29.6)	2342 (42.6)	1334 (75.7)	878 (118)	183 mammal species (P. Iloldi-Rangel, personal communication)	
Oaxaca(e)	78,262 (1.18)	19,836 (4.73)	5091 (18.9)	3299 (29.6)	2318 (42.6)	1341 (75.7)	875 (118)	57 environmental parameters (Hijmans et al. 2005)	
Québec(s)	33,967 (0.850)	23,474 (3.38)	12,940 (13.4)	10,125 (21.0)	8156 (30.1)	5589 (53.4)	3890 (83.3)	719 species (Sarkar et al. 2005)	
Québec(e)	33,967 (0.850)	23,474 (3.38)	12,940 (13.4)	10,125 (21.0)	8156 (30.1)	5589 (53.4)	3890 (83.3)	56 environmental parameters (Sarkar et al. 2005)	
Queensland(s)	3828 (1.18)	2227 (4.72)	931 (18.9)	693 (29.5)	518 (42.4)	350 (75.4)	251 (118)	2348 vascular plants (Sarkar et al. 2005)	
Queensland(e)	3828 (1.18)	2227 (4.72)	931 (18.9)	693 (29.5)	518 (42.4)	350 (75.4)	251 (118)	54 environmental parameters (Sarkar et al. 2005)	
Transvolcanic belt(s)	67,752 (1.16)	20,113 (4.65)	6012 (18.6)	4027 (29.1)	2942 (41.9)	1792 (74.5)	1205 (116)	99 mammal species (Fuller et al. 2006)	
Transvolcanic belt(e)	63,696 (1.16)	18,816 (4.65)	5757 (18.6)	3912 (29.1)	2827 (41.9)	1712 (74.5)	1154 (116)	59 environmental parameters (Hijmans et al. 2005)	
West Virginia(s)	65,970 (0.966)	16,773 (3.86)	4331 (15.4)	2810 (24.1)	1973 (34.8)	1144 (61.8)	747 (96.5)	323 species (Strager & Yuill 2002)	
West Virginia(e)	65,091 (0.966)	16,560 (3.86)	4299 (15.4)	2769 (24.1)	1961 (34.8)	1118 (61.8)	744 (96.5)	55 environmental parameters (Hijmans et al. 2005)	

*The e index refers to data sets of environmental parameters, and the s index refers to data sets of species records.

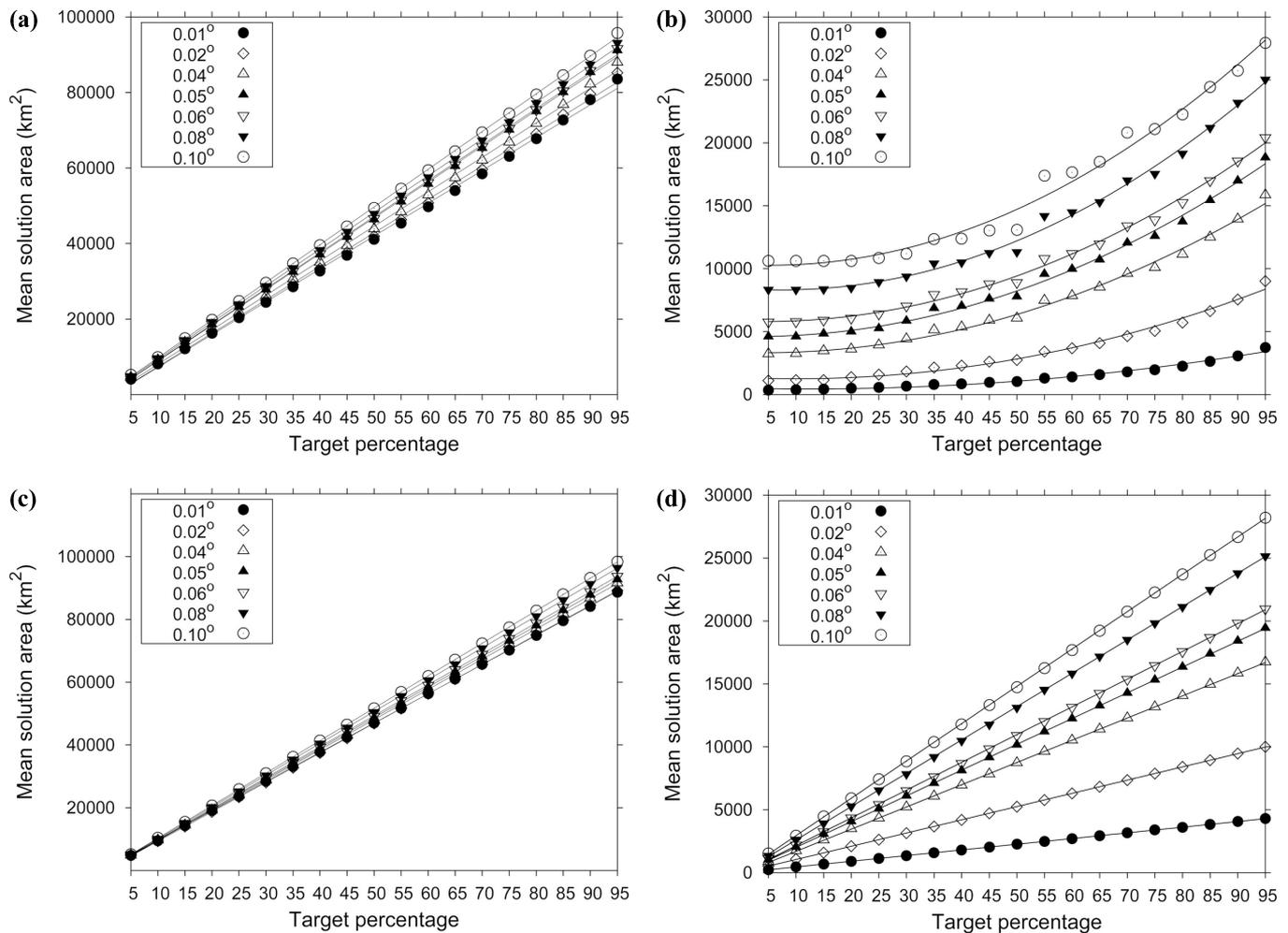


Figure 2. Effects of the percentage of target area on total area of conservation-area networks in (a) Oaxaca(s); (b) Queensland(s); (c) Oaxaca(e); and (d) Queensland(e) (s, data sets of species; e, data sets of environmental parameters). For (a-d) the y-axis represents the area of the conservation-area network selected. Each line represents the mean of the set of areas selected for 100 randomizations at a specific spatial resolution. Standard errors were too small to be depicted. The lines for (a), (c), and (d) are the best-fit linear regressions, $f = m \cdot t + b$, where f is area, t is target, and m and b are constants. In (b) lines are the best-fit polynomial regressions, $f = a \cdot t^2 + bt + c$, where f is area, t is target, and a , b , and c are constants (r^2 values not shown).

surrogates were assumed present if they were found in the finer-resolution areas comprising them.

Results

The total size of selected areas for data sets representing environmental parameters or modeled species distributions exhibited a linear dependence on target level for all spatial resolutions analyzed. Results for Oaxaca(s), Oaxaca(e), and Queensland(e) (Figs. 2a,c,d) were indistinguishable in this sense from those for the Korean Demilitarized Zone, the Mexican Transvolcanic belt(e,s), Québec(e), and West Virginia(e,s). Linear regression yielded $f = m \cdot t + b$, $m \in [45.13, 998.51]$ ($r^2 \geq 0.999$,

$p < 0.0001$) for all of these data sets at all 7 spatial resolutions, and m increased with resolution for all data sets. Approximately an order of magnitude difference was evident between the area required for 5% and 50% targets for all spatial resolutions and data sets.

Mexico, Queensland(s), and Québec(s) contained surrogate information from surveys and records and exhibited a nonlinear convex target-area relationship. Queensland(s) exhibited the most convex relationship, which became less pronounced at coarser resolutions (Fig. 2b). This increase in economy may reflect the fact that more species co-occur in a single area at coarser resolutions. Polynomial (quadratic) regression yielded highly significant results ($r^2 \geq 0.985$, $p < 0.0001$) for all 7 resolutions. The relatively horizontal lines for 5% through 50% targets indicated that up to approximately a 50% target for these

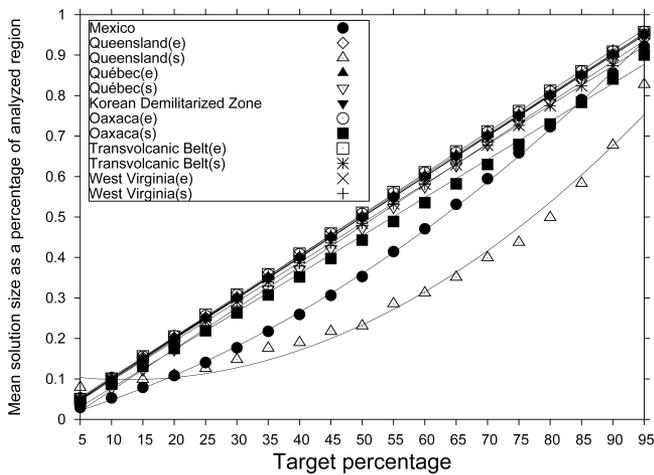


Figure 3. Effects of target on total area of conservation-area networks for all 12 data sets at the 0.01° spatial resolution. The y-axis represents the mean area of sets of areas selected expressed as a percentage of the region analyzed. Each curve represents the mean of the sets of areas selected for 100 randomizations at a specific spatial resolution. Standard errors are too small to be depicted. For Mexico(s) and Queensland(s), the quadratic model $f = a \cdot t^2 + bt + c$ provided the best fit (e, data sets of environmental parameters; s, data sets of species). For all other data sets, we obtained the best fit from the linear model.

plant species is achievable with fairly small increases in CAN area. Mexico showed a similar, although less convex, relationship for all resolutions ($r^2 \geq 0.999$, $p < 0.0001$). At finer resolutions, Québec(s) exhibited a linear relationship, but it became slightly convex at coarser resolutions ($r^2 \geq 0.998$, $p < 0.0001$). At each resolution, the percent variance in the mean solution area explained by the target level was greater for the polynomial than for the linear model.

Our regression analyses suggest that the differences in the target-area functions for the data sets depended on the type of surrogate data. In particular, the target-area function for Queensland(s) was nonlinear (piecewise convex), whereas Queensland(e) exhibited a linear target-area function (Figs. 2b,d & Fig. 3). This result is likely due to the fact that, typically, more species than environmental parameters co-occur in a single area at any resolution, and the extent of this co-occurrence increases at coarser resolutions. There were also many more species surrogates than environmental parameter surrogates. This added to the increased likelihood of overlap between Queensland(s) and Queensland(e).

The areas selected for Queensland(s) had higher spatial economy (lower total size) than those selected for Queensland(e) for all conservation targets $> 5\%$. This lack of economy of the areas selected to represent the en-

vironmental surrogates was most pronounced for mid-range targets. In particular, for the 50% target, the size of the areas selected for the environmental surrogates was more than twice the size of the areas selected for the plant species.

The lack of economy in area prioritization for the Queensland(e) was likely due to the large number of ties after the calculation of complementarity that arise for targets around 50%. In general, the number of ties with the use of rarity and complementarity may influence the linearity of the target-area function. The number of such ties depended on the number of surrogates, with fewer ties likely if there were more surrogates. Queensland(s) contained 43 times as many surrogates as Queensland(e). When the number of ties was large, more iterations of the rarity-complementarity algorithm were required to satisfy the targets for all the biodiversity surrogates. This led to a selection of more areas. For the Queensland data sets, when the conservation target was 50%, there were 2.2×10^5 ties after the calculation of complementarity in the Queensland(e) but only 1.7×10^3 such ties in Queensland(s). For the 50% target, 1450 iterations of the rarity-complementarity algorithm were required to satisfy the targets for half of the environmental parameters but less than one-third as many iterations were needed to meet the targets for half of the plant species. The properties that make CAN design problems computationally difficult are not well characterized (Sarkar et al. 2004). Nevertheless, when rarity-complementarity algorithms are used, the number of ties after the calculation of complementarity may be a better measure of problem difficulty than the number of biodiversity surrogates.

The CAN area increased with coarser spatial resolution for all data sets, but in different ways. The relationship between CAN area and spatial resolution for each target level for Québec(s) was concave (Fig. 4). Each curve in Fig. 4 represents a vertical cross section of Fig. 2b for each corresponding target level. The Korean Demilitarized Zone, Mexican Transvolcanic belt(e,s), Québec(e), and Queensland(e,s) exhibited a similar concave relationship. The Mexican Transvolcanic belt, Oaxaca(e,s), and West Virginia(e,s) showed a linear relationship. Mexico exhibited a slightly convex relationship.

Discussion

Our results demonstrate a linear relationship between CAN area and target level for a wide variety of surrogates and regions for all spatial resolutions analyzed. We expected mutually exclusive surrogates such as land types or vegetation classes to lead to linear relationships because, typically, land types and vegetation classes do not overlap spatially within areas. Our results for data sets of environmental parameters also exhibited a linear target-area function. Results of previous studies seem to

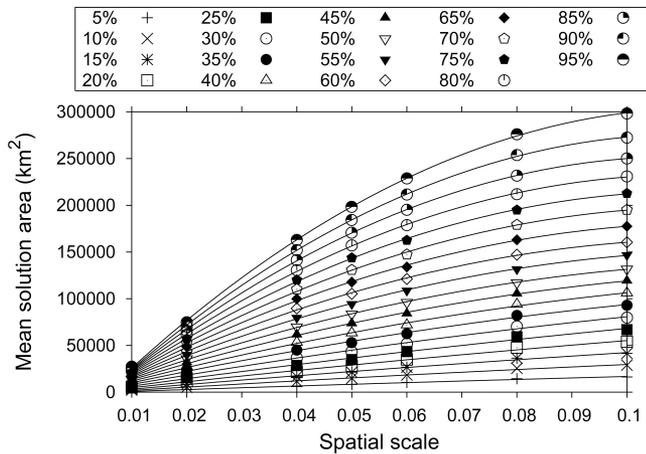


Figure 4. Effects of spatial resolution on total area of conservation-area networks for Québec(s) (s, data sets of species). The x-axis represents spatial resolution, and the y-axis represents the area of the conservation-area network selected. Each curve represents the mean of the sets of areas selected for 100 randomizations at a specific spatial resolution. Standard errors are too small to be depicted. Solid lines are the best-fit polynomial regressions, $f = a \cdot t^2 + bt + c$, where f is area, t is target, and a , b , and c are constants. For this data set, the r^2 associated with the polynomial model was greater than the r^2 associated with the linear model (Fig. 3)

support this finding. On the basis of area prioritization for 248 land types, Pressey and Logan (1998) found that CAN area increased linearly across 1, 5, and 10% targets at 3 spatial resolutions (specifically, areas of mean size 62, 172, and 1316 km²), although this inference should be treated with caution because there were only 3 data points. Nonmutually exclusive surrogates, such as modeled species distributions, however, also exhibited a linear target-area relationship. Warman et al. (2004) also found that the CAN area required for 29 vertebrate species increased with higher targets. Because the 3 targets of Warman et al. were not systematically related to one another and only one spatial resolution (10-km² hexagons) was analyzed, the functional form of the relationship and its sensitivity to spatial resolution could not be determined.

The slope of the linear target-area relationship we found also suggests that higher surrogate representation will usually require significantly more area. The best fit for most data sets was a linear function with slope much >1 . If scientifically defensible conservation targets exceed those adopted by policy organizations by a factor of 3, as a recent review suggests (Svancara et al. 2005), our results suggest 3 times more area is required for the higher targets. This supports the conclusion drawn by Svancara et al. (2005) that the mean CAN area required

for the scientifically defensible targets is 3 times that required for the targets adopted by policy organizations.

The protocol in Fig. 1 and the optimization model in Supplementary Material demonstrate how this type of analysis can provide grounds for target selection. The first step in the protocol (Fig. 1) is to construct a target-area curve. If the curve is linear, the next step is to ask whether the slope is low or high. If the slope is high, there is no alternative other than to construct context-specific models to establish appropriate targets. If the slope is low, the rational course of action is simply to select the largest target level permitted by the budget because it is worthwhile to invest in more area because this significantly increases biodiversity representation. Nevertheless, the curve may not be linear. In that case it will either be concave or convex. If it is the former, then once again it is worthwhile to invest in more area as before, and the largest target level allowed by the budget should be selected. If the curve is convex, the situation is more complicated and there are two choices: construct a context-specific model (if data are available) or solve the following optimization model.

When the target-area function is relatively horizontal, the target can be increased without increasing the area of the CAN significantly. The purpose of the optimization model is to select a target level that corresponds to a horizontal segment of this function. When there is more than one horizontal segment, the model selects the highest target associated with a horizontal segment. This is important for the practice of conservation planning because higher targets provide greater representation of the biodiversity surrogates. The model finds a relatively horizontal segment of the target-area function by comparing each segment to a flat line. In addition, the slope of the target-area function at the target selected by the model has to be between the average slope for lower targets and the average slope for higher targets. These constraints prevent the model from picking a very low target. Automating analysis of the target-area function via an optimization model is important because the number of functions that must be analyzed in practical planning contexts may be extremely large (our analysis required 156,000 area prioritizations).

This protocol is particularly relevant in cases such as that of the Queensland(s) data set, which was analyzed with the optimization model in some detail (Fig. 5). For these plant species, the required CAN area increased much less up to an approximately 50% target than after the 50% target was met. Targets used for practical CAN selection for these species should be set to at least 50% (assuming the land-acquisition budget permits this choice) because the higher representation better ensures persistence but costs comparatively less in terms of area. The optimization model described earlier generalizes this principle. If there is an approximately horizontal interval of the target-area function, targets should be set at their

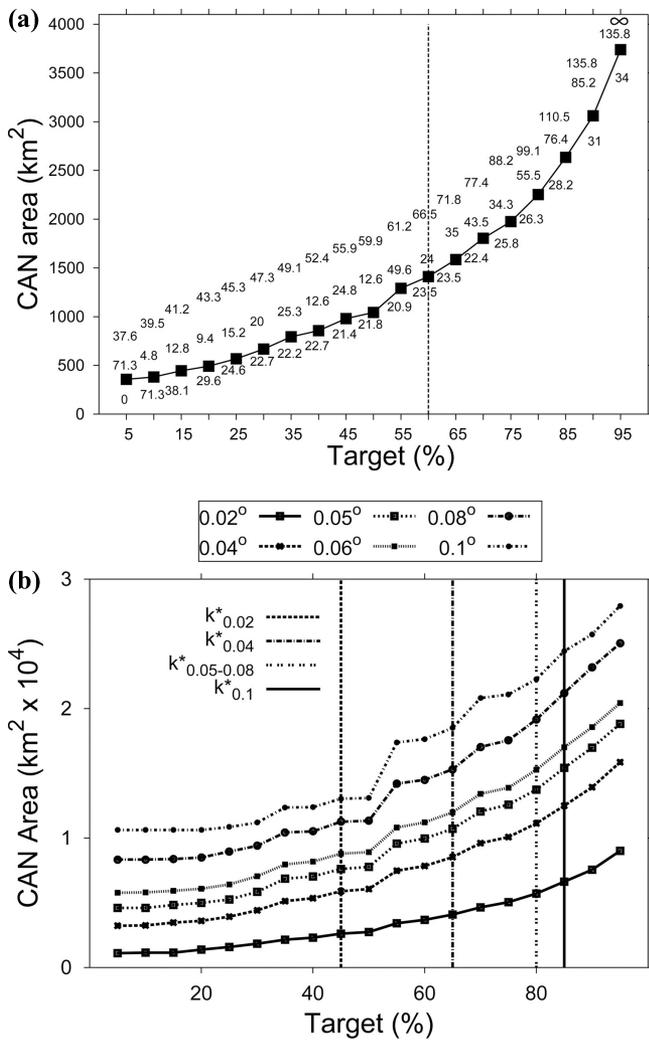


Figure 5. The selection of optimal targets with a convex target-area function. In (a) the solid line is the target-area function f for the Queensland plant species data at the 0.01° resolution (CAN, conservation-area network). The dashed vertical line shows the target selected by the optimization model (60%). The y-coordinate of the k^{th} black box is the required area of a conservation-area network when target k is used for all of the biodiversity surrogates. The first number above the k^{th} box is \bar{u}_k , the average slope of f for targets $>k$. The second number above the k box is b_k , the slope of f immediately to the left of k . The number below the k^{th} box is \bar{l}_k , the mean slope of f for targets $<k$. Boundary conditions are $\bar{l}_1 = 0$ and $\bar{u}_K = \infty$. See Supplementary Materials for details. Panel (b) shows the effect of spatial resolution on the target-area function for the Queensland plant data set: 0.02° – 0.1° . The x-axis is the conservation target, and the y-axis is the required size of the CAN. The vertical lines indicate the conservation target selected by the optimization model at each spatial resolution.

highest (right) value in this interval. We derived this rationale for setting targets solely from information on surrogate distributions. We did not base it on ecological studies of the plant species.

Our method thus complements recent efforts to tailor targets to the specific conservation status and ecology of individual species (Burgman et al. 2001; Pressey et al. 2003), such as the use of data on population size and trend (increasing, decreasing, or constant) to set targets for wildfowl in Mexico (Pérez-Arteaga et al. 2005). Tear et al. (2005) recently systematized these efforts in a conceptual framework for setting targets. Nevertheless, their methods can be used only when data on, for example, demography are available for all surrogates. Unfortunately, such data are typically unavailable when conservation planning concerns hundreds or thousands of species. Further analyses of the type presented here are needed to determine to what extent the difference between results obtained from data sets of survey record surrogate information and results from modeled species distributions can be generalized.

We did not consider the role of the area-cost function (g)—which assigns costs (in dollars) to amounts of land (Frazee et al. 2003)—may have on target selection. In most practical conservation planning, area is the only available measure of cost. Further studies of area-cost relationships are needed, however, and may provide a justification for target selection similar to the rationale we present (see Ando et al. 1998; Polasky et al. 2001; Naidoo et al. 2006). Similarly, several other factors that we did not consider may influence the choice of target level, for instance, availability of areas for conservation action, possible spatial configurations, and various sociopolitical factors (Sarkar et al. 2006; Margules & Sarkar 2007). Our analysis should be regarded as a first step in developing guidelines for selection of representation targets in the absence of adequate data to construct context-specific models.

Our results also illustrate the importance of choice of spatial resolution in conservation planning. Like Pressey and Logan (1998), we found that CAN area increased at coarser spatial resolutions. Thus, the decisions obtained with the protocol in Fig. 1 will depend on the spatial resolution of a planning exercise. Nevertheless, for different data sets, the area increased with spatial resolution in different ways: concavely, linearly, and (slightly) convexly. If the relationship was concave, at coarser resolutions the extent of the increase in CAN area decreased. Similar to the rationale for target selection, a concave resolution–area relationship may provide a rationale for selecting a spatial resolution at which conservation planning should be conducted. Specifically, because conservation-area networks at coarser resolutions contain larger areas, and larger areas may better ensure the persistence of species surrogates, a sufficiently concave

resolution–area relationship may justify increasing the land-acquisition budget b to conduct conservation planning at coarser spatial resolutions.

Acknowledgments

We thank C. Margules for helpful conversations, C. Kelley, M. Munguía, P. Illoldi-Rangel, V. Sánchez-Cordero for providing data sets, and R. L. Pressey for very useful comments on an earlier draft. This work was supported by National Science Foundation (U.S.A.) grant SES-0645884, 2007–2009.

Supplementary Material

The optimization model (Appendix S1) is available as part of the on-line article from <http://www.blackwell-synergy.com/>. The author is responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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