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 five 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 seven 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 indicates how total area increases 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 based on the functional form of target-area relationships. In particular, the method shows how the target-area relationship can provide a rationale for setting targets based solely on distributional information about surrogates.

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 socio-economic concerns and the processes which threaten conservation goals, implementing these algorithms in practical planning contexts requires specification of quantitative targets: minimal levels of representation of features of conservation interest, such as species, other taxa, or vegetation types. Targets are typically specified as the total size (in km^2) of areas in a CAN required to contain different surrogates or proportions of distributions of surrogates required to be represented in the CAN. Without explicit, quantitative targets the adequacy of conservation plans cannot be evaluated properly (Pressey et al. 2003).

Ideally, the choice of the second type of target should 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 multi-species 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). A recent review argues: “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” (Tear et al. 2005, 835).

Without an adequate understanding of what species persistence requires, target choices are typically made for non-biological 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 recent studies have begun addressing this issue. Pressey and Logan (1998) found that total CAN area for land-systems in New South Wales increased with target level and spatial scale for two scales and three 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) developed a method based on simple population models for setting targets to ensure the persistence of vascular plants. It produced targets of 100%, 100%, and 54% of the distributions of three Queensland plant species. Other recent studies show at least 40–50% of habitats are required to ensure persistence (Fahrig 2001; Flather & Bevers 2002). Pressey et al. (2003) proposed 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 using a species-area relationship, finding that targets of 14–30% of 42 vegetation types in the Succulent Karoo (South Africa) were required to represent 70–80% of plant species. The targets established in the last two 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. However, even these representation targets are implicitly geared towards ensuring persistence even though they do not explicitly address the ecological processes that are involved.

Most of these new methods focus on setting targets for specific biodiversity surrogates, and require additional data about their demography, abundance, and other vital statistics. While these data should be used whenever available, since they are often not, especially when large numbers of surrogates are used, we propose a new method based on 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 which may not have been used as surrogates in the analysis that are conferred protection by protecting the surrogate (Pressey et al. 2003). Our analysis is based on a target-area function *f*, which assigns amounts of land (in units of km^2) to CANs at different target levels, and an area-cost function *g*, which assigns costs (in units of $) to amounts of land. The function *f* is important because it can be directly computed using any area prioritization algorithm as shown later in this paper. Thus, if *t* is the target of representation, *f*(*t*) is the area of the CAN that is needed. Then *g*(*f*(*t*)) is the cost of that area of land. Consider fixed land-acquisition budgets first. Since higher representation targets increase the likelihood of persistence of surrogates, targets should be set at the maximum level t^* permitted by the budget *b*. To compute t^*, set the budget $b = g(f(t^*))$. This equation allows *b* to be calculated if t^* is known. However, we need to compute t^*

when we know the budget b. We, therefore, solve the inverse of this equation to get the maximum permitted target level, $t^* = f^{-1}(g^{-1}(b))$.

If the budget b is not fixed and may be increased in order 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 potentially be used for target selection. In particular, suppose $f = m \cdot t$, where t is the target and m is a constant (that is, f is a linear function). Then the slope m of the line 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. However, for $m >> 1$, greater representation requires significant increases in area. Appropriate targets should then be selected using 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 and 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 greater targets require smaller increases in area. If f is convex, we may construct context-specific models if the required data are available. If not, note that f may be modeled as a sequence of relatively horizontal line segments (for an example, see Figure 5, which is explained in detail in the "Discussion"). When f is relatively horizontal, we can increase the target without significantly increasing the area of the CAN (similarly for relatively horizontal portions of a concave target-area function). We present an optimization model that selects a target associated with relatively horizontal segments of f when the function is convex (Appendix 1).

The small number of data sets, targets, surrogates, and spatial scales analyzed in previous studies prevented systematic determination of f. We compute f for 12 data sets at seven spatial resolutions and 19 target levels.

Methods

Each data set consists 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 $P = (p_{ij})\,(i = 1,\ldots,n; j = 1,\ldots,q)$, where $p_{ij} = 1$ if the j-th surrogate is found in the i-th area; otherwise, $p_{ij} = 0$. The regions analyzed include: 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 based on 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 km^2) 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 and Margules 2002). The algorithm was iterated until the targets for all surrogates were satisfied. Since 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. Since such a large number of area prioritizations cannot be performed using an optimal solver in a reasonable amount of time, the fast rarity-complementarity heuristic algorithm of ResNet was used. However, to ensure that results are not artefacts of the algorithms used, the hardest problems (using species surrogates at finest resolutions for the larger data sets—Mexico, Queensland, Québec, Transvolcanic Belt) were also solved using an optimal solver (CPLEX). Optimal solutions were uniformly only marginally better (< 1 %) of the heuristic solutions (data not shown; see, also, Fuller et al. 2006).

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

To assess how spatial resolution affects the target-area relationship, each data set was prioritized at seven spatial resolutions: 0.01° longitude × 0.01° latitude, 0.02°×0.02°, 0.04°×0.04°, 0.05°×0.05°, 0.06°×0.06°, 0.08°×0.08°, and 0.10°×0.10°. For areas at coarser resolutions, 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 parameter or modeled species distributions exhibit a linear dependence on target level for all spatial resolutions analyzed. Results for Oaxaca(s), Oaxaca(e), and

Queensland(e) (Figure 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 data sets at all seven 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) contain 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 (Figure 2b). Polynomial (quadratic) regression yielded highly significant results $(r^2 \geq 0.985, p < 0.0001)$ for all seven resolutions. The relatively horizontal lines for 5–50% targets indicate that up to approximately a 50% target for these plant species is achievable with fairly small increases in CAN area. Mexico showed a similar, though 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 $(r^2 \geq 0.998, p < 0.0001)$. For these three data sets, the r^2 associated with the polynomial model was greater than the r^2 associated with the linear model. This increase in economy may reflect the fact that more species co-occur in a single area at coarser resolutions. Figure 3 shows the target-area functions for all data sets with the mean total size of the selected areas expressed as a proportion of the total size of the data set.

Our regression analyses suggest that the differences in the target-area functions for the data sets depend upon the type of surrogate data. In particular, the target-area function for Queensland(s) is non-linear (piecewise convex) whereas Queensland(e) exhibits a linear target- area function (Figure 2b,d; Figure 3). This result is likely due to the fact that, typically, more species than environmental parameters co-occur in a single area at any scale, and the extent of this co-occurrence will increase at coarser resolutions. There are also many more species surrogates than environmental parameter surrogates. This adds to the increased likelihood of overlap in Queensland(s) over Queensland(e).

The areas selected for Queensland(s) have higher spatial economy (lower total size in km^2) than those selected for Queensland(e) for all conservation targets greater than 5%. The lack of economy of the areas selected to represent the environmental surrogates is most pronounced for mid-range targets. In particular, for the 50% target, the size of the areas selected for the environmental surrogates is more than twice the size of the areas selected for the plant species.

The lack of economy in area prioritization for the Queensland(e) is 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 after using rarity and complementarity may influence the linearity of the target-area function. The number of such ties depends on the number of surrogates, with less ties be likely if there are more surrogates. Queensland(s) contains 43 times as many surrogates as Queensland(e). When the number of ties is large, more iterations of the rarity-complementarity algorithm are required to satisfy the targets for all of the biodiversity surrogates. This leads to a selection of more areas. For the Queensland data sets, when the conservation target is

50%, there are 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, 1 450 iterations of the rarity-complementarity algorithm are required to satisfy the targets for half of the environmental parameters but less than one-third as many iterations 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). However, when rarity-complementarity algorithms are being utilized, the number of ties after the calculation of complementarity may be a better measure of problem difficulty than the number of biodiversity surrogates.

CAN area increased with coarser spatial resolution for all data sets, but in different ways. Figure 4 shows the concave relationship between CAN area and spatial resolution for each target level for Québec(s). Each curve in Figure 4 represents a vertical cross section of Figure 2(b) 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. Mutually exclusive surrogates such as land-types or vegetation classes are expected to lead to linear relationships because, typically, land-types and vegetation classes do not overlap within areas. Our results for data sets of environmental parameters also exhibit a linear target-area function. Results from previous studies seem to support this finding. Based on area prioritization for 248 land-types, Pressey and Logan (1998) found that CAN area linearly increased across 1%, 5%, and 10% targets for three spatial scales (specifically, areas of mean size 62, 172, and 1316 km^2) though this inference should be treated with caution since there are only three data points. Non-mutually 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. Since the three targets were not systematically related to one another and only one spatial resolution (10-$km.^2$ hexagons) was analyzed, the functional form of the relationship and its scale sensitivity 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 greater than 1. If scientifically defensible conservation targets exceed those adopted by policy organizations by a factor of three, as a recent review suggests (Svancara et al. 2005), our results suggest three times more area is required for the higher targets. This supports Svancara et al.' s (2005) conclusion that the mean CAN area required for the scientifically defensible targets is three times that required for the targets adopted by policy organizations.

The protocol presented in Figure 1 and the optimization model presented in Appendix 1 demonstrate how this type of analysis can provide grounds for target selection. Figure 1 depicts a decision tree. The first step 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 since it is worthwhile to invest in more area because this significantly increases biodiversity representation. However, 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 permitted by the budget should be selected. If the curve is convex, the situation is more complicated and there are two choices: (i) either construct a context-specific model (if data are available); or (ii) 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 is required 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 is analyzed with the optimization model in some detail (Figure 5). For these plant species, the required CAN area increases much less up to an approximately 50% target than afterwards. Targets used for practical CAN selection for these species should be set at at least 50% (assuming the land-acquisition budget permits this choice) since the higher representation would better ensure persistence but cost comparatively less in terms of area. The optimization model described above generalizes this principle. If there is an approximately horizontal interval of the target-area function, targets should be set at their highest (right) value in this interval. Notice that this rationale for setting targets was derived solely from information on surrogate distributions. It was not based on ecological studies of the plant species.

The method presented here 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 using 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. However, these methods can only be used 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 in results obtained for data sets containing survey and record surrogate information and those containing modeled species distributions can be generalized.

Our analysis did not consider the role the area-cost function *g*, which assigns costs (in units of $) to amounts of land (Frazee et al. 2003), may have in 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 do not consider may influence the choice of target level, for instance, availability of unit areas for conservation action, possible spatial configurations, and various socio-political factors (Sarkar et al. 2006; Margules and Sarkar 2007). The analysis presented here should be regarded as a first step in developing guidelines for representation target selection 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 using Figure 1 will depend on the spatial resolution of a planning exercise. However, for different data sets, the area increased in different ways: concavely, linearly, and (slightly) convexly. If the relationship is concave, at coarser resolutions the extent of the increase in CAN area decreases. Similar to the rationale for target selection a concave target-area relationship may provide, a concave resolution-area relationship may provide a rationale for selecting a spatial resolution at which conservation planning should be conducted. Specifically, since 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.

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Table 1

Properties of data sets analyzed.

Data set	**Number of areas** (Mean area size in 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	21109 (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)	78511 (1.18)	19961 (4.73)	5123 (18.9)	3323 (29.6)	2342 (42.6)	1334 (75.7)	878 (118)	183 mammal species (P. Illoldi-Rangel, personal communication)
Oaxaca(e)	78262 (1.18)	19836 (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)	33967 (0.850)	23474 (3.38)	12940 (13.4)	10125 (21.0)	8156 (30.1)	5589 (53.4)	3890 (83.3)	719 species (Sarkar et al. 2005)
Québec(e)	33967 (0.850)	23474 (3.38)	12940 (13.4)	10125 (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)	67752 (1.16)	20113 (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)	63696 (1.16)	18816 (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)	65970 (0.966)	16773 (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)	65091 (0.966)	16560 (3.86)	4299 (15.4)	2769 (24.1)	1961 (34.8)	1118 (61.8)	744 (96.5)	55 environmental parameters (Hijmans et al. 2005)

Figure Captions

Figure 1: Flowchart of target selection using the target-area function. *m* denotes the slope of *f* **,** the target-area function. How targets should be selected depends upon the functional form of the target-area relationship. (For more details, see the text ["Discussion"].)

Figure 2: Effects of target percentage on total area of conservation area networks in (a) Oaxaca(s); (b) Queensland(s); (c) Oaxaca(e); and, (d) Queensland(e). For (a-d), the *x*-axis ranges from 5% to 95% targets at 5% increments, and the *y*-axis represents the area of the conservation area network selected. Each curve 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. As spatial resolution increases for these data sets, *m* increases, i.e. the linear regressions grow steeper. 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. At each scale, the percentage variance in the mean solution area explained by the target level is greater for the polynomial than for the linear model (r^2 values not shown).

Figure 3: Effects of target percentage on total area of conservation area networks for all twelve data sets at the 0.01° spatial resolution. The *x*-axis ranges from 5% to 95% at 5% increments, and 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 were 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 For all other data sets, we obtained the best fit from the linear model.

Figure 4: Effects of spatial resolution on total area of conservation area networks for Québec(s). 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 were too small to be depicted. The 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. At each resolution the percentage variance in the mean solution area explained by the scale was greater for the quadratic than for the linear model (r^2 values not shown). As target level increases for these data sets, *a* increases.

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° scale. 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 $\overline{u}_k$, the average slope of *f* for targets greater than k. The

second number above the k^{th} 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 less than k. We impose the boundary conditions that $\bar{l}_1 = 0$ and $\bar{u}_K = \infty$. See Appendix 1 for details. Panel (b) shows the effect of scale on the target-area function for the Queensland plant data set: 0.02°-0.1°. *x*-axis: conservation target; *y*-axis: required size of the conservation area network ($\text{km}^2 \times 10^4$). The vertical lines indicate the conservation target selected by the optimization model at each scale.

Appendix 1

We present an optimization model for selecting a target to be used in conservation planning when the target-area function f is piecewise convex. Let $k = 1 \ldots K$ be indices for the targets and t_k be the numerical value of target k (e.g., 10%). Let a_k denote the area (in km^2) of a conservation area network selected with target k for each surrogate. Further, let b_k signify the slope of f to the left of target k: $b_k = \frac{a_k - a_{k-1}}{t_k - t_{k-1}}$. Note that if t_k is converted to units of km^2 then b_k is a dimensionless quantity that represents the effect of increasing the target from $k-1$ to k on the required size of the conservation area network. When f is relatively horizontal, the target can be increased without increasing the required area of the conservation area network substantially. Thus, one of the desiderata of the optimal target k^* is that the slope of f be as horizontal as possible to the left of k^*.

However, if f consists of more than one relatively horizontal line segment, it is desirable for conservation purposes to select the highest target that corresponds to a relatively horizontal segment of f. The Introduction explains why higher targets are desirable from a conservation standpoint.

We include the following constraints in the optimization model to ensure that the model selects as high a conservation target as possible. Let $\bar{l}_k$ denote the average slope of the target-area function for targets less than k, i.e. $\bar{l}_k = \frac{1}{k-1}\sum_{j=1}^{k-1} b_j$, and let $\bar{u}_k$

symbolize the average slope for targets greater than k, i.e. $\bar{u}_k = \frac{1}{K-k}\sum_{j=k+1}^{K} b_j$. When the target level k is small, $\bar{l}_k$ tends to be greater than $\bar{u}_k$. Our optimization model requires that the selected target level k^* must have the property that $\bar{l}_{k^*} \le b_{k^*} \le \bar{u}_{k^*}$. The model also requires that b_{k^*} be as horizontal as possible. If f has more than one relatively horizontal line segment, these requirements pick the highest target associated with a relatively horizontal segment. For example, the target-area function of the Queensland plant data set (Figure 2) is relatively horizontal for the 10% target ($b = 4.81$), the 35% target ($b = 25.26$), and the 60% target ($b = 24$); however, only for the 60% target is b at least as large as the average slope for smaller targets ($\bar{l} = 23.47$) and no greater than the average slope for larger targets ($\bar{u} = 66.53$). We formulate the optimization model as follows:

$$\text{minimize} \quad \sum_{k=1}^{K} w_k \qquad (1)$$

$$\text{subject to} \quad w_k \ge b_k x_k - 1, \quad k = 1,\ldots,K \qquad (2)$$

$$\sum_{k=1}^{K} x_k = 1 \qquad (3)$$

$$b_k x_k \le \bar{u}_k + M y_k, \quad k = 1,\ldots,K \qquad (4)$$

$$-b_k x_k \le M y_k - \bar{l}_k, \quad k = 1,\ldots,K \qquad (5)$$

$$x_k \le M(1 - y_k), \quad k = 1,\ldots,K \qquad (6)$$

$$x_k \in \{0,1\}, \qquad k = 1,\ldots,K \qquad (7)$$

$$y_k \in \{0,1\}, \qquad k = 1,\ldots,K \qquad (8)$$

$$w_k \geq 0, \qquad k = 1,\ldots,K \quad (9)$$

For each target k, constraint (2) computes the difference between one and the slope of the target-area function f associated with k (recall that a function with a slope of one is horizontal). Together with constraint (2), the non-negativity constraint (9) captures $\max\{0, b_k x_k - 1\}$, where $b_k x_k - 1$ is the difference between the slope of a horizontal line and the slope of the target-area function to the left of target k. The objective of the model (constraint 1) is to pick a target k such that this difference is as small as possible. Constraint (3) requires that exactly one target level be selected for use in the conservation plan. x_k is a binary decision variable set equal to one if target k is selected for use in the conservation plan and set equal to zero otherwise. Constraints (4)-(6) require that for each target level k either $\bar{l}_k \leq b_k \leq \bar{u}_k$ or $x_k \leq 0$. That is, we can only select a target k if the slope of f to the left of k is between the average slope for targets less than k and the average slope for targets greater than k. M is a large positive constant and y_k is a dummy variable; both are used to formulate either-or constraints (Hillier & Lieberman 2001).

Hillier, F. S. and G. J. Lieberman. 2001. Introduction to Operations Research. Seventh Edition. McGraw-Hill, Boston.