Flexibility, efficiency, and accountability: adapting reserve selection algorithms to more complex conservation problems

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Flexibility, efficiency and accountability are considered key attributes of good reserve selection methods. Flexibility, the ability to incorporate all the diversity of considerations, concerns and information that typically impinge on real conservation problems, is fundamental if the particulars of any given situation are to be addressed and land use conflicts are to be effectively resolved. High efficiency, the representation of the maximum diversity of the relevant features (e.g. species) at the minimum cost, is important because reserves will commonly be in direct competition with other forms of land use. Accountability means that the solutions are obtained in a transparent way, allowing others to understand why and how the result was arrived at. Because of the robustness of the general integer linear model, a remarkably rich variety of problems concerning the management and efficient use of scarce resources can be represented as problems of this type. This study starts by analysing a simple representation problem and then develops more general problems that can be applied to a variety of conservation planning exercises. It is illustrated how high flexibility can be attained, while simultaneously addressing efficiency and accountability, by modelling reserve selection questions as integer linear problems.


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In this paper, we illustrate how flexibility, efficiency and accountability can be addressed simultaneously in reserve selection procedures by modelling them as integer linear problems. For simplicity, throughout we treat “species” as the features of interest, but most of the considerations apply equally to other features, such as “land types” (Pressey et al. 1996, 1997), “plant communities” (Cocks and Baird 1989, Bedward et al. 1992, Nicholls and Margules 1993) and “environmental domains” (Bedward et al. 1992, Pressey and Tully 1994).

Addressing flexibility

Integer linear programming deals with problems of maximising or minimising a linear function of variables subject to inequality and/or equality constraints and integrality restrictions on some or all of the variables. Because of the robustness of the general model, a remarkably rich variety of problems concerning the management and efficient use of scarce resources can be represented as linear integer problems (Nemhauser and Wolsey 1988).

The basic problem: to represent each species at least once in the minimum number of sites

Representing each species at least once in the minimum number of sites is the conservation planning problem addressed most frequently in the literature (e.g. Saertsdal et al. 1993, Kershaw et al. 1994, Margules et al. 1994, Lombard et al. 1995, Castro Parga et al. 1996, Williams et al. 1996b, Cutsi et al. 1997, Pressey et al. 1997, Hacker et al. 1998, Nantel et al. 1998). This is a well known 0/1 linear programming problem: the set covering problem (Padberg 1979, Balas 1980, Balas and Ho 1980, Underhill 1994, Ando et al. 1998) and can be written as:

Minimise \( \sum_{j=1}^{n} x_j \) \hspace{1cm} (I)

Subject to \( \sum_{j=1}^{n} a_{ij}x_j \geq 1, \quad i = 1, 2, \ldots, m \) \hspace{1cm} (II)

\( x_j \in \{0, 1\} \quad j = 1, 2, \ldots, n \) \hspace{1cm} (III)

where \( n \) is the number of sites, \( m \) is the number of species, \( a_{ij} \) is 1 if species \( i \) is present in site \( j \) and 0 otherwise, and variable \( x_j \) is 1 if and only if site \( j \) is selected.

The objective function (I) is to minimise the number of sites selected. Inequalities (II) ensure that each of the \( m \) species must be present at least once. The integrality restrictions (III) state that each variable \( x_j \) is either 0 or 1, forcing each site to be treated as an indivisible unit (thereby avoiding solutions that would select fractions of each site).

Defining a higher representation target: represent each species at least \( b \) times in the minimum number of sites

Typically, representation in just one site will clearly be insufficient to ensure the long-term persistence of all species in a reserve network (Rodrigues et al. 2000). It is possible to set a higher representation target by changing the restrictions represented by inequalities (II). When the target is to represent each species at least \( b \geq 1 \) times (e.g. Margules et al. 1988, Pressey and Nicholls 1989a, b, Rebelo and Siegfried 1992, Williams et al. 1996a, Willis et al. 1996, Freitag et al. 1998), the restrictions are:

Subject to \( \sum_{j=1}^{n} a_{ij}x_j \geq b, \quad i = 1, 2, \ldots, m \) \hspace{1cm} (II)

Note that it may not be possible to find a minimum set for the each-species-once target among the subsets of a minimum set for higher representation targets. In addition, and this is perhaps more disappointing, it may happen that no minimum set satisfying constraints (II) is obtained by adding sites to an optimal solution of the each-species-once problem. Consider the following matrix \([a_{ij}]\), describing which species 1, 2, 3 are present in each site \( s_1, s_2, s_3, s_4 \).

\[
\begin{bmatrix}
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
0 & 1 & 1 & 1 \\
\end{bmatrix}
\]

All three species do not occur simultaneously in one single site. Since all occur in \( \{s_1, s_2\} \), this is an optimal set of sites for the each-species-once problem. If we want to obtain a solution for the each-species-twice by adding sites to \( \{s_1, s_2\} \), we are forced to use the two remain sites \( s_3 \) and \( s_4 \). Yet, each species is present twice in \( \{s_1, s_3, s_4\} \).

Thus, whilst it has been argued that a method which identifies a network that represents each species at least once provides a core of areas that can subsequently be expanded (e.g. Nicholls and Margules 1993, Margules et al. 1994), the set which results if this is done may not necessarily be the most efficient network for attaining a higher target.
When sites have different sizes: represent each species at least once in the minimum area

Thus far we have assumed that all sites are equally relevant, i.e., the coefficient of every variable $x_j$ in the objective function (I) is equal to 1. This is often the case, since many analyses are based on occupancy data mapped on grids, all grid cells have the same area and are considered to have the same cost of acquisition (e.g. Rebelo and Siegfried 1992, Lombard et al. 1995, Castro Parga et al. 1996, Williams et al. 1996a, b, Willis et al. 1996, Freitag et al. 1997, Hacker et al. 1998, Nantel et al. 1998). However, it may be desirable to consider the implications of differences in the cost of different networks, for example when sites are of different sizes (e.g. Pressy and Nicholls 1989b, Bedward et al. 1992, Saetersdal et al. 1993, Margules et al. 1994, Turpie 1995, Pressey et al. 1997) and/or when sites differ in monetary value (e.g. Ando et al. 1998). In this set covering problem, the objective function (I) is replaced by:

Minimise $\sum_{j=1}^{n} c_j x_j$,  \hspace{1cm} (I')

where $c_j$ is the cost of site $j$ (usually, but not necessarily, the area).

Assigning different targets to species: represent each species $i$ at least $b_i$ times in the minimum area

The reserve selection problems considered thus far, like most addressed in the literature, assume that all species should receive the same investment. Several algorithms do deal with species weighted differently. Examples are rarity-based algorithms (e.g. Pressy and Nicholls 1989b, Rebelo and Siegfried 1992, Kershaw et al. 1994, Castro Parga et al. 1996), those that take taxonomic distinctiveness into account (e.g. Vane-Wright et al. 1991, Kershaw et al. 1994), and the algorithm applied by Freitag et al. (1997) which uses a ranking of species according to their conservation importance (Freitag and van Jaarsveld 1997). However, these weightings influence only the order in which sites are selected (by resolving ties), with those sites containing priority species tending to be selected first. The final representation target is generally the same (usually each species once) for all species, which means that the integer linear formulation is the same as without species weighting.

 Species prioritisation makes sense if used to allocate limited conservation resources to the features that most need protection. This can easily be achieved by setting higher representation targets for priority species (as in Kirkpatrick 1983). Ideally, such targets are an expression of the level of representation required in the reserve network for the long-term persistence of each species (Bedward et al. 1992). The priority value for each species can be determined using single (e.g. rarity, taxonomic distinctiveness) or multi-criteria evaluation systems (e.g. Freitag and van Jaarsveld 1997), or by existing classifications such as the IUCN Red List categories (Anon. 1994). When working with other biodiversity features, such as plant communities or environmental domains, priority can be determined in terms of rarity (e.g. inversely related to the frequency of occurrence or total extent in the region) or threat (e.g. a measure of fragility or risk of short-term destruction).

For the problem where each species is represented a predefined number of times according to its priority, inequalities (II) must be modified to:

$$\sum_{j=1}^{n} a_{ij} x_j \geq b_i, \hspace{1cm} i = 1, 2, \ldots, m \hspace{1cm} (I'')$$

which states that the number of selected sites in which each species $i$ must be represented is at least $b_i$.

Problem (I) subject to (I''), (III) is called the multi-covering problem (Hall and Hochbaum 1992), a generalisation of the set covering problem.

Giving sites different values: represent each species in at least a given percentage of its range in the minimum area

When working with sites with different areas, a target of representing each species a given number of times may be misleading. By requiring a species to be present once, for example, no distinction is made between selecting a large site comprising most of its geographical range or a small one comprising only a small proportion. Indeed, since we aim at a minimum area, the tendency is to select the smallest possible sites. Assuming a homogenous density across the range of a species, a larger site will contain a higher proportion of its population, and will therefore, all else being equal, make a higher contribution to its conservation in the long-term. As a first approximation, the relative importance of a site to the persistence of a species may therefore be expressed in terms of the fraction of its range contained in the site. The problem of representing each species in at least a given percentage, $b_i\%$, of its range in the minimum area can be expressed as (I') subject to (I''), (III):

Minimise $\sum_{j=1}^{n} c_j x_j$,  \hspace{1cm} (I')

Subject to $\sum_{j=1}^{n} a_{ij} x_j \geq b_i, \hspace{1cm} i = 1, 2, \ldots, m \hspace{1cm} (I'')$

$x_j \in \{0, 1\} \hspace{1cm} j = 1, 2, \ldots, n. \hspace{1cm} (III)$
but now $a_{ij}$ is the percentage of the range of species $i$ in site $j$, and not, as before, a binary value of presence or absence. This is a general 0/1 linear programming problem.

Defining the same target for all species in terms of percentage of range (e.g. Nicholls and Margules 1993, Kirkpatrick and Brown 1994, Pressey and Tully 1994, Pressey et al. 1997) may be a bad strategy in conservation terms. In practice, it means that the absolute target for a rarer species is lower than for a common one (30% of a small range is <30% of a large one), meaning that a higher conservation investment is being made in relatively unimportant species. Therefore, when using a percentage of range as a target, it is advisable to establish different values for each biodiversity feature (as in Lombard et al. 1997), ideally proportional to the conservation investment we want to allocate them. A very rare species (e.g. a narrow endemic) may require protection in 100% of its range, while a species that has declined greatly and has at the present non-viable populations may require >100% of its range reserved (e.g. for habitat restoration and reintroduction).

### Working with densities: represent at least a given percentage of the population of each species in the minimum area

The ranges of species are typically not homogenous in terms of ensuring their long-term persistence, some areas being more important than others. When density data are available, and assuming that species tend to be more abundant in sites which are more important for their survival, these provide an objective measure of the importance of each site. Ideally, a system of reserves should capture the sites with higher densities (Rodrigues et al. 2000), or eventually compensate for the selection of less adequate sites by selecting a larger area.

One possible approach is that followed by Kershaw et al. (1994) and Turpie (1995), who for the purposes of area selection considered species to be present in a site only when they occurred there in substantial populations. But this implies a loss of information, since it results in the deletion of real occurrences (those below the population threshold) from the database. It also means that each site is either considered sufficient for the persistence of the species or totally irrelevant, which often is not the case. A more useful approach is to incorporate a continuous measure of the importance of sites, based on the continuous values of density.

Assuming that each species is homogeneously distributed across each site in which it occurs, the population size of each species in each site is obtained simply by multiplying the site’s area by the local density of the species. The total population is the sum of these values for all sites. The fraction of the overall population in each site may be used as a measure of the importance of the site to the species.

The problem of representing each species by at least $b_i$ % of its population in the minimum area can be expressed in the same way as the previous problem ((I) subject to (I’), (III)). But $a_{ij}$ is now the percentage of total population of species $i$ in site $j$, while the target $b_i$ is the minimum percentage of the population of species $i$ that must be protected in the selected set of reserves.

If the population size of each species in each site is known, then the target for each species can also be defined in terms of a minimum number of individuals (as in Nicholls 1998). However, to address the problem of representing at least a given percentage of the population of each species it is not essential to know absolute densities or number of individuals. Any abundance values can be used if given on a linear interval scale (i.e. doubling the relative abundance corresponds to a doubling of the real density). Also, values do not need to be comparable between species (only between sites for the same species), thereby avoiding the problem that values may be better reflections of absolute density for some species (e.g. those that are more conspicuous) than for others.

Instead of abundance, other measures of the importance of sites to each species can be used if the assumption is met that doubling the value means doubling the importance. For example, for a bird it may perhaps be considered that the nesting sites are five times more important than the foraging areas. Another possibility is to use as measures of importance the values derived from models of the probability of occurrence of a species at different sites (Williams 1998), or priority may be given to sites in the core of a species’ range (Nicholls 1998). When working with biodiversity features other than species, the importance of each site for each feature may, for example, be measured as the percentage of the range of each feature that exists in each site or by an index of its relative conservation status in each site.

### Further flexibility

All reserve selection problems presented thus far are particular cases of the general 0/1 linear programming problem ((I) subject to (I’), (III)). Despite its simplicity and conciseness, this is a sufficiently flexible model to include a variety of other requirements which may be desirable to consider in the context of reserve selection (see also Cocks and Baird 1989, Possingham et al. 1993, Church et al. 1996). For example: 1) if $m_j$ is the monetary value of site $j$, the constraint stating that the total monetary cost should not exceed a certain amount $M$ is:
\[ \sum_{j=1}^{n} m_j x_j \leq M. \]

2) If S is a given subset of sites (say, for instance, owned by the state), the imposition that at least a fraction p of the total area should belong to S is attained with the inequality:

\[ \sum_{j \in S} c_j x_j \geq p \sum_{j=1}^{n} c_j x_j, \]

which, in the format of the inequality constraints (II) can be equivalently rewritten as:

\[ \sum_{j=1}^{n} a_j x_j \geq 0, \quad \text{where } a_j = \begin{cases} (1-p)c_j & \text{if } j \in S \\ -pc_j & \text{if } j \notin S. \end{cases} \]

3) Since each species is represented by an independent set of restrictions, not only different targets but also different levels of information can be used for different species. For a threatened species with no abundance data, the target may be to be represented in 80\% of its range, for a species with good census data, the target may be of at least 1000 individuals, a value that may even have been obtained from population viability analysis, as suggested by Nicholls (1998).

4) For more complex integer linear problems it is unlikely that several optimal solutions exist, but it may be possible to explore the flexibility of reserve networks (in the sense given by Pressey et al. 1993) by obtaining near-optimal solutions. It is possible to prevent a given set S of s sites from being selected by adding a restriction that explicitly excludes it:

\[ \sum_{j \in S} x_j \leq s - 1. \]

When an optimal solution of a specific problem is excluded, the algorithm will find another optimal solution, if it exists, or else the second best result. By successively adding a restriction that excludes the previous solution, a sequence of different networks with equal cost or near to the optimal value is obtained. This diversity of solutions can afterwards be explored in order to address concerns that were difficult to include in the formal model, such as connectivity or specific land use conflicts.

As Nicholls (1998) concluded, it is more likely that the future of area-based selection methods is limited by lack of data than by our ingenuity to interface the data with the methods. Where possible, future fieldwork must be directed towards collecting useful data for conservation planning.

### Addressing efficiency: optimal and heuristic solutions

Efficiency is the attribute of a good reserve selection procedure to which reference is most frequently made (e.g. Reebel and Siegfried 1992, Bedward et al. 1992, Saetersdal et al. 1993, Kershaw et al. 1994, Lombard et al. 1995, Castro Parga et al. 1996, Willis et al. 1996, Ando et al. 1998, Freitag et al. 1998, Hacker et al. 1998, Nantel et al. 1998). Maximum efficiency can only be achieved by using algorithms that guarantee the attainment of optimal solutions. Since the set of solutions is finite, one could think of finding the optimum by simply enumerating all the possible solutions. However, even for moderate sized problems, enumerating is completely impractical. On a 40 MIPS computer, enumerating all the 2^n subsets of \{1, 2, \ldots, n\} (assuming that each subset requires no more than one single instruction) takes ca 14 min for n = 15 and ca 7 h for n = 20. But for n = 30 it would take > 800 yr.

Mathematical programming gives the proper tools for dealing with integer linear programming problems. Unfortunately, for many integer problems, such as the ones presented above and even for the particular case of set covering (I)–(III), there is little hope that algorithms which always perform better than complete enumeration can be designed (these problems are proved to be NP-hard, which is widely assumed to mean that their computational time increases exponentially with the size of the input, see Garey and Johnson 1979).

In most situations, a considerable reduction in the size of the data set may result from applying some simple pre-processing rules (Nemhauser and Wolsey 1988). Some rules were suggested by Possingham et al. (1993) and Camm et al. (1996) for the problem of representing each species once in the minimum number of sites. A more general set of rules that can be applied to any of the problems referred to above is: 1) to identify the irreplaceable sites: look for all the sites such that if removed from the analysis at least one of the species would exist in the remaining area below its required target. Irreplaceable sites are selected and excluded from the analysis, and the targets for all species occurring in those places must be updated. All species whose targets become zero or negative must be excluded. 2) To identify the redundant sites: some sites may contain only species that have been eliminated in the previous step. These are sites that make no contribution to the representation of the remaining species, and can therefore be excluded from the analysis.

These simple rules can permit a substantial reduction in the size of a data set. For example, when applied to the problem of representing 125 wetland plant species (including 25 considered rare) in 68 fens in the Scottish Borders (Rodrigues et al. 1999), they reduced the data matrix to: 16 species and 45 sites for the problem of...
representing each species once in the minimum area; 9 species and 24 sites for the problem of representing each of the rare species four times and each of the others once in the minimum area; 11 species and 37 sites for the problem of representing each of the rare species in 60% and each of the others in 10% of its range in the minimum area.

Reduction is normally effective because there is usually some degree of coincidence between sites with the rarer species, those with high diversity and those with high abundances (these are often the well preserved habitats, with less human interference). The irreplaceable sites, which usually depend on the presence of rarer species, are often sufficient also to fulfill the representation targets for many of the most widespread species, resulting in several species being removed from the analysis. Other sites that contain only those same widespread species become redundant and can be ignored. This outcome is more marked when the conservation targets are higher for the rare species (see example above), since it tends to increase the number of irreplaceable sites.

When, despite pre-processing, problems are too large to be solved in a reasonable time period by algorithms which guarantee an optimal solution, heuristics may be the only sensible option. Their ability to produce quick answers as part of interactive systems, such as CODA (Bedward et al. 1992) and WORLDMAP (Williams 1996), may be important for real-time evaluation of different reserve networks.

However, heuristics such as the ones that have been commonly used in conservation literature may not be the most appropriate from an efficiency perspective. These algorithms consist of stepwise procedures and comprise more or less intuitive rules to decide which site to add at each step (e.g. Margules et al. 1988, Nicholls and Margules 1993, Csuti et al. 1997, Pressey et al. 1997). It is generally stated that some of these are “good” heuristics that produce results that are only slightly sub-optimal (e.g. Pressey et al. 1996, Csuti et al. 1997, Williams 1998, Nantel et al. 1998). However, the degree of sub-optimality has been reported to vary widely (see Table 1), from heuristics that found the exact minimum (Willis et al. 1996) to situations where heuristic algorithms have produced grossly sub-optimal solutions (Saetersdal et al. 1993, Csuti et al. 1997, Pressey et al. 1997). The drawback of these particular heuristic methods is that although in some cases they can produce very good results, or even the optimal solution, there is no certainty that they will always perform well. The fact that one heuristic achieved a good result in a specific situation is not a guarantee of its efficiency in all cases (one good result does not make a “good” heuristic), since this is highly dependent on particulars of data structure (Pressey et al. 1996, Willis et al. 1996). For example, Saetersdal et al. (1993) applied the same heuristic to two distinct datasets and obtained a large discrepancy in the degree of sub-optimality of the results: 5% extra area for plants, and 43.3% for birds (Table 1).

The only way to know exactly how sub-optimal is the result obtained by an heuristic in a given situation is to assess it against the optimal result. Naturally, when this is possible there is no need for the heuristic in the first place. However, it is possible to evaluate the quality of the solutions (of a minimisation problem) produced by an heuristic by comparing it with a lower bound – a value that is known to be below or equal to the true (unknown) optimal value. The difference between the value of the heuristic solution and the lower bound is an upper bound of the distance between the heuristic solution and the optimal value, and therefore a measure of its quality.

Methods for obtaining good lower bounds (near the optimal) are fundamental in mathematical programming, not only for evaluating the quality of heuristic solutions but also for obtaining optimal solutions. Exact methods for the resolution of hard integer problems are essentially variations of the well-known enumerative “branch-and-bound” method, and their efficacy results mainly from the ability to find good lower bounds (for more details see Nemhauser and Wolsey 1988).

A way of obtaining a lower bound to the optimal value of a (minimisation) problem is by solving some easy relaxation, i.e. a new problem that contains all the solutions of the initial one. A continuous linear relaxation of a 0/1 linear problem is the one obtained when replacing the integrality constraints $x_i \in \{0, 1\}$ by $0 \leq x_i \leq 1$. The new problem is a standard linear programming problem, for which an optimal solution can be quickly obtained. Usually, this is not a 0/1 solution (if it were, then it would be an optimal solution of the integer problem), but its value is surely a lower bound to the 0/1 optimal value. However, the bounds thus obtained are normally far from the optimal value, which means that they are not good bounds.

It can be proven that given a solution $R$ of a relaxation which is not a solution of the original linear problem, there is always some linear inequality which “cuts” $R$, i.e. a new restriction that is violated by $R$ but verified by all the solutions of the original integer problem. The new problem obtained by adding this new inequality to the current relaxation is still a relaxation (again an easy linear programming problem) of the original problem, whose optimal solution is a better (or equal) lower bound than the previous one. Proceeding in this way a sequence of non-decreasing lower bounds to the optimal solution of the integer problem is obtained. This general procedure is called a cutting-plane algorithm (see for example Nemhauser and Wolsey 1988). Its efficacy depends on the ability to find suitable cuts. Nemhauser and Wolsey (1988) describe a family of cuts (strong cover inequalities) which produces excellent lower bounds.
“Intuitive” heuristic algorithms, such as many of those that have been used in the conservation literature, have the advantage of being easy to understand and to program. But for increasingly complicated problems they become more difficult to create. For example, where representation targets for different species are measured in different units, because of differences in the information available, (e.g. percentage of range, percentage of population, number of individuals), it is not straightforward to create a “good” heuristic. In these situations, it is also more likely that simple intuitive heuristics will perform poorly in terms of efficiency. Therefore, although for these more complex (more realistic) problems the processing time increases, it may very well be that here particularly the need to apply optimisation tools becomes more imperative.

Fortunately, mathematical programming is providing improved optimisation programmes, some of which are capable of dealing with large data sets and making use of approximation tools to reach the optimal solution faster. Also, they can be used as heuristic algorithms to obtain a sub-optimal solution. If processing time extends beyond reasonable limits, the programme can be interrupted and the best solution obtained meanwhile can be considered to be a heuristic result. Most optimisation programmes will also give the value of the best lower bound obtained so far, therefore providing a good measure of the degree of sub-optimality of this solution. One possible strategy may be to consider to be satisfactory any solution which has a maximum degree of sub-optimality of, say, 5% and interrupt processing as soon as it is obtained.

Many programmes also accept as input the value of a known feasible solution that is an upper bound of the optimal value. This can reduce considerably the processing time by eliminating a priori the more expensive solutions. The solution obtained by an heuristic (including an “intuitive” one) can therefore be used as an initial upper bound, and the result obtained after some processing time is never worse than the initial one. In

Table 1. Summary of the results of examples of published studies that assessed the efficiency of heuristic algorithms by comparing them with optimal solutions (partially adapted from Pressey et al. 1996). In the two last examples, the optimal solution was not found but results are given to illustrate the variability of solutions obtained by the heuristics. In the analysis by Csuti et al. (1997) and Pressey et al. (1997), the values for heuristics correspond to the best results out of 100 runs for each algorithm, and not to the average result.

<table>
<thead>
<tr>
<th>Study</th>
<th>Objective</th>
<th>Results</th>
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| Saetersdal et al. (1993), Norway | To represent each of 321 plant species at least once in the minimum number of woods (out of 60). | Optimal: 71.4% of total area  
Heuristic: “nearly 75%” of total area  
The heuristic found 5% more area than the optimal solution |
| Saetersdal et al. (1993), Norway | To represent each of 47 bird species at least once in the minimum number of woods (out of 60). | Optimal: 27.9% of total area  
Heuristic: 40% of total area  
The heuristic found 43.4% more area than the optimal solution |
| Willis et al. (1996), South Africa | To represent each of 110 plant species at least once in the minimum number of grid cells (out of 53). | Optimal: 13 cells  
Heuristics: 13 cells  
The heuristics found the optimal solution (n = 2) |
| Csuti et al. (1997), USA | To represent each of 426 terrestrial vertebrates at least once in the minimum number of hexagons (out of 441). | Optimal: 23 sites  
Heuristics: between 24 and 29 sites  
The heuristics found between 4.4% and 26.1% more sites than the optimal solution (\(\mu = 9.2\%; \sigma = 6.1\%; n = 18\)) |
| Pressey et al. (1997), Australia | To represent each of 248 land system at least once in the minimum number of pastoral holdings (out of 1885). | Optimal: 54 sites  
Heuristics: between 57 and 81 sites  
The heuristics found between 5.6% and 50% more sites than the optimal solution (\(\mu = 19.4\%; \sigma = 15.2\%; n = 12\)) |
| Pressey et al. (1997), Australia | To represent each of 248 land system at least once in the minimum area of pastoral holdings (out of 1885). | Optimal: 12 084.50 km²  
Heuristics: between 13 359.75 and 16 958.25 km²  
The heuristics found between 10.6% and 40.3% more area than the optimal solution (\(\mu = 21.6\%; \sigma = 10.0\%; n = 12\)) |
| Pressey et al. (1997), Australia | To represent at least 5% of the total regional extent of each of 248 land system in the minimum number of pastoral holdings (out of 1885). | Optimal: not found  
Heuristics: between 123 and 157 sites  
The worst heuristic found 27.6% more sites than the best one (\(\mu = 7.2\%; \sigma = 8.0\%; n = 18\)) |
| Pressey et al. (1997), Australia | To represent at least 5% of the total regional extent of each of 248 land system in the minimum area of pastoral holdings (out of 1885). | Optimal: not found  
Heuristics: between 25 887.5 and 30 756.25 km²  
The worst heuristic found 18.8% more area than the best one (\(\mu = 8.3\%; \sigma = 4.9\%; n = 18\)) |
this way, optimisation programmes can be used to improve the result obtained by a heuristic.

The decision about how to obtain a solution for a specific situation will depend mainly on the reserve selection problem in hand. In some situations, an assumedly non-optimal solution might be all that it is possible to attain, but if so a measure of sub-optimality should be provided. For most problems, however, an optimal solution should probably be possible to obtain in a reasonable time. How long is “reasonable” is variable and mainly a trade-off between the importance of having a quick result vs having an exact solution. In real conservation problems, where the cost associated with a worse solution is a real concern, it might be worth waiting for some days to obtain a cheaper result.

This focus on obtaining more efficient solutions does not mean that concern about cost should be the priority when addressing real conservation planning problems. As far as possible, the first step must be to decide what should be the problem that is to be solved (i.e. determine the ecological constraints) and then make the best possible use of optimisation techniques to look for the less costly solutions. The purpose of applying these methods to conservation planning is not that less money is invested in the acquisition of reserves, but that the amount available is invested in a more effective way.

Addressing accountability

Modelling reserve selection questions as integer linear problems by using mathematical programming tools can bring substantial advantages in terms of the accountability of the results.

The formal writing of integer linear problems requires that conservationists make very explicit the goals to be achieved by a reserve network. The objective function clearly states what is the variable that should be optimised (usually a measure of cost) and the restrictions identify the constraints that must be imposed on the network. Potentially subjective values, such as the investment to be allocated to each species or the relative importance of each site, are necessarily made explicit. In this way, an integer linear problem expresses unequivocally the problem being solved, resulting in more explicit solutions. This is particularly relevant in more complex situations, where it becomes more difficult to devise appropriate “intuitive” heuristics that correspond to the problem in hand. For example, Pressey et al. (1997) did not develop specific heuristics for each of the problems of minimising the total area in a network and of minimising the total number of sites. Instead, they used the same algorithms for both, therefore obtaining necessarily identical solutions. Furthermore, by solving a formally written problem there is a guarantee that all the concerns addressed are taken into account in the result. With “intuitive” heuristics, however, there is less clarity in this regard. Issues such as valuing species differently (Freitag et al. 1997) or minimising the total area rather than the total number of sites (e.g. Pressey et al. 1997), have been incorporated into heuristic approaches in the form of rules to solve ties. This assumes that ties will occur, but in more complex problems this may not happen. When ties exist, it is unpredictable how each concern will really influence the final result, because it depends on the frequency of ties, on the “hierarchy” of each concern in the tie-resolving rules and often on random decisions.

Finally, the optimality of the solution is itself a guarantee of more transparency in the results. For example, when adding a new constraint to a minimisation problem, the new optimal solution is never less costly than the original one, which allows an exact measure of the cost associated with a specific constraint. The sub-optimality of heuristics brings uncertainty to detailed comparative analyses of efficiency, because variance obtained in the costs of the solutions of two problems does not necessarily reflect real differences in cost. The higher the degree of sub-optimality of the solution obtained by the heuristic the more serious this problem can be, and in extreme situations, it may even lead to an inversion of the expected results (e.g. in Pressey and Tully 1994). Even in the situations where an optimal solution is not achieved, it is useful to have a measure of the quality of the solution obtained (a lower bound), in order to assess the reliability of the conclusions taken from the result.

Conclusions

Most reserve selection exercises reported in the literature have focused on relatively simple problems, such as that of representing each species once or a fixed number of times. However, most real conservation scenarios are likely to be considerably more complex, in order to reconcile all of the concerns prevailing and to use all the relevant information available. In order to ensure the long-term effectiveness of reserve networks, it is essential that considerations arising from ecological theory, at the population, community or landscape levels, are integrated in selection algorithms (Nicholls 1998), including issues such as viability and threat (Williams 1998). Otherwise, reserve selection procedures will inevitably result in approaches that are too simplistic from the perspective of the conservation agencies, compromising their credibility as valuable tools for application in real-life conservation problems.

This paper illustrates how a wide diversity of considerations and information can easily be integrated in
reserve selection procedures when they are modelled as integer linear problems. Many of the issues discussed, such as valuing species and sites differently, do not presuppose the existence of higher levels of information than those commonly available in real situations. Indeed, in most regions where detailed information on the distribution of species exists (enough for the application of the classical complementarity methods), other relevant data is also accessible but has usually been ignored. For example, most countries have Red Data books before they have distribution atlases, and at least for some species there is information on the most relevant sites for their conservation, sometimes resulting from population viability analysis. Therefore, the higher complexity advocated in this paper does not correspond in most situations to a need to obtain more information, but to make the best use of the available data when selecting a network of reserves.

More complexity implies more difficulty in creating adequate “intuitive” heuristics for the specific problem in hand, therefore risking an even higher level of sub-optimality and reducing the explicitness of the results. Mathematical programming techniques provide a more effective way of improving the flexibility of reserve selection algorithms without compromising the efficiency and accountability of the results.

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