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Optimality in reserve selection algorithms: When does it matter and how much?

R. L. Pressey, H. P. Possingham, C. R. Margules

This paper responds to recent criticisms in *Biological Conservation* of heuristic reserve selection algorithms. These criticisms primarily concern the fact that heuristic algorithms cannot guarantee an optimal solution to the problem of representing a group of targeted natural features in a subset of the sites in a region. We discuss optimality in the context of a range of needs for conservation planning. We point out that classical integer linear programming methods that guarantee an optimal solution, like branch and bound algorithms, are currently intractable for many realistic problems. We also show that heuristics have practical advantages over classical methods and that suboptimality is not necessarily a disadvantage for many real-world applications. Further work on alternative reserve selection algorithms is certainly needed, but the necessary criteria for assessing their utility must be broader than mathematical optimality.

Introduction

From a mathematical viewpoint, optimal reserve selection algorithms are those that identify the smallest set of sites, in terms of number or total area, needed to represent a targeted group of natural features in a region. The importance of optimality is largely that it minimizes the cost of achieving a reservation goal, both in terms of acquisition of land for conservation and foregone opportunities for other land uses, Optimality means maximum efficiency of representation in terms of the number or area of selected sites (Pressey & Nicholls, 1989). It also means maximum complementarity of sites. Complementarity has been proposed as an important principle of reserve selection (Vane-Wright *et al.*, 1991; Pressey *et al.*, 1993). It refers to the need, once a representation target has been set, for new reserves to complement previous ones as fully as possible in the features they contain rather than to duplicate features unnecessarily.

Given equal competing land use pressures, political support and funding, an optimal solution should increase the likelihood, compared to a suboptimal one, of achieving a fully representative reserve system. The size of this advantage is likely to depend, of course, on the extent to which departures from optimal representation are necessary to deal with real-world constraints. These constraints include other reservation criteria such as spatial arrangement and land suitability and the compromises involved in turning algorithm selections into actual reserves on the ground.

Another advantage of optimality is that algorithms that achieve it are most reliable for comparative purposes. They can be used to compare alternative reservation scenarios (e.g. starting with or without certain sites) and alternative data bases (e.g. the same region mapped at two scales). Differences between scenarios in the optimal required number or area of sites can be confidently ascribed to the factors being tested rather than to inconsistencies in the operation of the algorithm on different data sets.

Analyses that can identify optimal sets of sites to achieve representation goals are clearly desirable. Classical methods for solving integer linear programming problems, like the branch and bound approach promoted by Underhill (1994), can guarantee optimal representation of natural features, at least for some data sets and some problems (see Lawler & Wood, 1966 for a description of these methods). We agree with Underhill (1994) that heuristic algorithms cannot guarantee optimal solutions, although they can be demonstrated to achieve or approach optimality. Indeed, we can define heuristics for the purposes of this paper as analytical methods that proceed in steps designed intuitively to find optimal or near-optimal solutions, but without the ability to confirm optimality. Does this lack of guaranteed optimality mean that heuristics have limited value in conservation planning and that classical optimizing methods are 'the strand of progress in reserve selection algorithms that ought to be pursued' (Underhill, 1994)? These questions would be easy to answer if they depended only on which algorithm was optimal when applied to a simple reserve selection problem.

The question of the relative utility of alternative selection algorithms actually depends not only on mathematics but also on the practicalities of conservation planning. In this paper, we address this important question by considering the following issues: (1) the degree of suboptimality of heuristics; (2) the tractability of alternative algorithms for realistic problems; (3) the comparative value of optimal and suboptimal analyses for indicative purposes; (4) the comparative value of optimal and suboptimal analyses in the full planning context; and (5) the need to rank priorities for protection. We refer to classical methods for guaranteeing solutions to integer linear programming problems as 'optimizing algorithms'. As an alternative to these, there are several possible heuristic approaches used to approximate optimal solutions. One that has been widely applied in reserve selection is the 'greedy' algorithm specifically criticized by Underhill (1994). This is a stepwise analysis that selects sites for notional reservation according to how many previously under-represented features they contain (e.g. Kirkpatrick, 1983; Vane-Wright *et al.,* 1991). It seeks the highest increment of new features at each step, making 'locally' optimal decisions that do not necessarily add up to a 'globally' optimal solution for representing all the features in a region. A similar stepwise heuristic is based on the relative rarity of features (e.g. Margules *et al.,* 1988), beginning with sites that have unique features and progressively adding those that contain the next rarest under-represented features. It also progressively makes locally optimal selections in an attempt to achieve or approach a global optimum. Another heuristic approach is the genetic algorithm (Holland, 1975). Simulated annealing (Kirkpatrick *et al.,* 1983) is sometimes considered a heuristic method. We use the term 'heuristic' to refer to stepwise greedy and rarity algorithms, unless otherwise specified, since these are the approaches that have been most commonly applied in systematic conservation planning.

Issues Relating To Optimality Of Algorithms In Conservation Planning

Suboptimality of heuristics

Cocks and Baird (1989) were the first to demonstrate that optimizing algorithms could find a smaller solution to a reserve selection problem than a heuristic (applied by Margules & Nicholls, 1987). This has caused some users of heuristics subsequently to refer to their solutions in terms such as 'relatively small' (Pressey & Nicholls, 1989) and 'near-minimal' (Pressey *et al.,* 1993) and to regard heuristics as approaching or being guided by the principle of complementarity (Vane-Wright *et al.,* 1991; Pressey *et al.,* 1993) rather than fully achieving it.

Two of us have compared the results of 12 heuristic algorithms, differing in their selection rules, with optimal solutions (Pressey *et al.,* in press). We used a data set of the occurrence of 248 land types in 1885 pastoral holdings in the Western Division of New South Wales. The problem for the algorithms was to select a set of sites that represented each land type at least once. There was no requirement for a minimum percentage area of each land type. We found that a 'good' heuristic (with purposeful rules directed at efficient representation) selected a number of sites slightly larger than optimal and a 'bad' heuristic (lacking very purposeful rules) selected substantially more than the optimal number (Table l(a)). In terms of site area, the best heuristic selected sites that totalled about 10% more than optimal (Table l(a)). Saetersdal *et al.* (1993) obtained similar results in Norway for minimum total area of sites (Table l(b)) but their heuristic found the optimal numbers of sites needed to represent two sets of species. Comparative results for vertebrate species in Oregon (Csuti *et al.,* in press) were similar to those from the Western Division (Table l(c)).

Simulated annealing found the same sized solution as an optimizing algorithm for the Western Division data set (Ian Ball, pers. commun.), although the same general approach did slightly less well than stepwise heuristics in Oregon (Csuti *et al.,* in press). A recent study in south-western California (Church *et al.,* 1996) found that a heuristic algorithm could represent all vertebrate species in the same number of 162 km 2 quadrangles as an optimizing algorithm. Willis *et al.* (1996) also showed that two heuristics could produce optimal results for equal-sized sites (eighth-degree grid cells) in South Africa. They considered that the gap between the results of heuristics and optimizing algorithms will be narrowed or closed if, as in their study area, a large proportion of a region's features are narrow endemics. This type of distribution forces alternative algorithms to select very similar sets of sites. Many of the plant species analysed by Saetersdal *et al.* (1993) were regionally endemic to one site and this could at least partly explain the ability of their heuristic to select a total area of sites for plants that was closer to the optimal solution than in the Western Division (Table l(a),(b)).

Table 1. Minimum numbers and areas of sites selected by alternative algorithms; bracketed figures are percentage increases relative to optimal solutions

[a] This study: pastoral holdings in western New South Wales (out of 1885) needed to represent each of 248 land types at least once

Algorithm[a]	Number	Area (km^2)
Branch and bound (optimal)	54	12,085
'Good' heuristic	57 (5·6)	13,360 (10·6)
'Bad' heuristic	81 (50·0)	16,958 (40·3)

[a] different heuristic algorithms produced the smallest solutions for area and number

b. Sætersdal *et al.* (1993): deciduous woods in part of Norway (out of 60) needed to represent each of 321 plant species and 47 bird species at least once

	Algorithm	Number	% Total area
Plants	Branch and bound (optimal)	32	71·4
	Heuristic	32	'nearly 75' (5)
Birds	Branch and bound (optimal)	12	27·9
	Heuristic	12	40 (43·4)

c. Csuti *et al.* (in press): hexagons, each 635 km^2 (out of 441) needed to represent each of 426 terrestrial vertebrates breeding in Oregon

Algorithm	Number
Branch and bound (optimal)	23
'Good' heuristic	24 (4·4)
'Bad' heuristic	29 (26·1)

Several other characteristics of data sets could also affect the suboptimality of heuristics, including the average size and size range of sites. For example, the large difference between the optimal area to represent birds in the Norwegian woods and the area selected by the heuristic (Table l(b)) was due to the addition on one very large site that contained no endemics (Saetersdal *et al.,* 1993). Another factor could be the nestedness of species or other features that determines the relative efficiencies of heuristics on different data sets (Ryti, 1992). Other comparisons of optimizing algorithms and heuristics in reserve selection have been on small demonstration data sets. These have shown that heuristics can fail to select optimal sets of sites that can be identified by hand (Possingham *et al.,* 1993: Underhill, 1994). Nevertheless, it remains to be demonstrated that any of the studies criticized by Underhill (1994) used algorithms that were 'grossly suboptimal' which he considers heuristics can be. More importantly, an assessment of the utility of alternative algorithms must consider the implications of suboptimality for their potential uses in conservation planning. Demonstrating that optimizing algorithms are 'better' than heuristics for a simple representation problem leaves many questions about practical value unanswered. We consider these below.

Tractability for realistic problems

Optimizing algorithms minimize the value of an objective function (e.g. the number of sites in the final solution) subject to a number of constraints that impose limits on the choice of solution. The constraints for a simple representation problem are derived, for example. from a table of species presence-absence data (Saetersdal *et al.,* 1993). For each species, a constraint is defined that requires any valid solution to include at least one occurrence of the species. Other examples of linear constraints are total site areas or acquisition costs that should not be exceeded. Optimization problems are 'NP-complete' which means that their computation time increases roughly exponentially with the number of constraints. No algorithms are available to circumvent this exponential increase in the time needed to guarantee an optimal solution.

Reserve selection problems for small to medium-sized data sets are therefore relatively easy and quick to solve with optimizing algorithms once the package has been properly formulated. Optimal solutions to simple representation problems were found in a few minutes for a data set of 441 sites and 426 species in Oregon (Csuti *et al.,* in press) and in seconds for a data set of 280 sites and 333 species in south-western California (Church *et al.,* 1996). For larger problems, the processing time could be prohibitive, depending on how quickly an answer is required. For example, an optimal number of sites needed to give at least one representation of each of the 248 land types in the Western Division (1885 pastoral holdings) was found by a previous version of LP SOLVE (Freeware from Michel Berkelaar, Eindhoven University of Technology, Department of Electrical Engineering, Design Automation Section, PO Box 513, NL-5600 MB

Eindhoven, Netherlands) after about 10 days' computation on a SUN IPX workstation (Possingham *et al.,* 1993), although equally small solutions (without guaranteed optimality) were found much more quickly. A more recent version of the same package found an optimal number of sites in about 10 h. Single runs of the heuristics applied to the same problem produced answers in 5 min or less on a 486 desktop (Pressey *et al.*, in press). These were prototype programs that have now been optimized for processing time to run in seconds. On the same data set, simulated annealing selected the same number of sites as the optimizing algorithm but in a fraction of the time (Ian Ball, pers. commun.). Time differences of this magnitude are highly significant for practical conservation planning. If a reserve selection algorithm is part of a decision-support system (see below) and managers and politicians are waiting to see the results of some alternative scenario that they have suggested, computation time of more than a few minutes becomes a serious impediment to the planning process. The ability of heuristics to produce quick answers as parts of interactive systems (e.g. Williams *et al.,* 1991; Bedward *et al.,* 1992; Pressey *et al.,* 1995) is extremely important for real-time investigation of alternative reservation scenarios.

Other more complex reserve selection problems are even less amenable to solution by optimizing algorithms and can be intractable with current methods. For the Western Division data set, a much more realistic problem than the one analysed for Table l(a) is to represent a minimum percentage of the total area of each land type. This could be a blanket target, such as 5% of all land types, or targets graded in some way according to factors such as risk of degradation or previous decline. Without percentage area targets, the requirement of a simple occurrence is likely to leave many land types inadequately represented in selected sites.

The same problem applies to representation of any other natural features. Is one or even three or five occurrences of each species in a set of nominal protected areas really an effective reservation goal? The population size of at least some species in selected sites is likely to be dangerously small, even if such a goal were achieved. Representation goals for species would be more usefully framed in terms such as population size, where data are available, or the selections could be restricted to local populations known to be larger than some threshold value (Kershaw *et al.,* 1994). Ideally, representation goals for species should also be combined with data on source areas (Pulliam, 1988) and patches of critical resources (Pressey, 1994). We found two widely used packages for optimization (with the branch and bound method) to be unworkable for the percentage area problem for land types in the Western Division, even when we reduced the number of sites in the data set by more than 75%. The packages were LP_SOLVE (see details above) and LINGO, a major commercial package. The packages ran on SUN IPX workstations for weeks without finding solutions. The 18 heuristics we trialled for this problem, before optimizing for speed, found solutions for the full data set in minutes on a 486 desktop, as for the presence-absence problem. For small data sets, optimal solutions to percentage area and other quantitative representation problems can also be found by adapting the combinatorial analyses of Pressey *et al.* (1994) which yield much useful information in addition to the identity of the optimal set(s).

The reserve selection problems discussed by Underhill (1994) are linear because the constraints and costs are linear in terms of the control variable. Other problems will be far more complex. The problem becomes non-linear if, for example, the boundary of the reserve system needs to be minimized. The difficulty of finding an optimal solution and the necessary computation time increase dramatically.

One way of making a large reserve selection problem manageable for optimizing algorithms is to reduce the data matrix (Possingham *et al.,* 1993; Camm *et* a/.,1996). The approach taken by Possingham *et al.* (1993) involved two rules for data reduction:

(1) remove every site that contains a set of species that is a subset of, or is equivalent to, the set of species in another site; and (2) remove every species that occurs in a set of sites that is a superset of, or is equivalent to, the set of sites in which another species occurs.

This approach can work well for simple presence/absence problems requiring at least one occurrence of each species or some other feature. However, for more complex and realistic problems, and particularly for non-linear problems, it can be less useful or ineffective. One of us (H.P.P.) is developing genetic algorithms and simulated annealing methods for reserve selection problems that are more difficult than presence-absence goals for small data sets. So far, simulated annealing has given better solutions to some problems than other heuristics. It could be a practical compromise between optimizing algorithms and the commonly used stepwise heuristic -- it produces reasonable answers in reasonable time and can produce better answers if left to run for longer. It is notable that heuristics are, of necessity, the methods used by many mathematicians working on complex applied problems in operations research. They develop heuristics that are tested against optimizing algorithms for relatively small and simple problems and then apply them to larger and more complex ones. For complex problems, heuristics can be superior to optimizing algorithms because of faster computation and the likelihood of actually obtaining an answer, even if it is not guaranteed to be optimal.

Comparative value of alternative algorithms for indicative analyses

Any reserve selection algorithm, used alone, has only indicative value as a starting point for further considerations. The realities of conservation planning require selection algorithms to deal with more complex problems than simple representation of natural features. Furthermore, computers do not produce networks of reserves that are already acquired, politically acceptable, and with boundaries and natural features confirmed on the ground (Bedward *et al.,* 1992; Margules *et al.,* 1994). For some time, optimizing approaches in the general area of resources planning have been seen as indicative, rather than prescriptive, tools (Cocklin, 1989) and this applies equally well to heuristics. There are also advantages in having algorithms nested within larger systems for supporting decisions on reserve acquisitions. Algorithms alone can, however, be useful in comparing reserve requirements under different conditions. A valuable type of comparison is to compare the total land area needed to represent all targeted features in a region starting both with and without a set of existing or proposed *ad hoc* reserves. The required area including *ad hoc* reserves is typically larger than that when the analysis begins without them which provides an estimate of the cost of such decisions (Margules & Nicholls, 1987; Cocks & Baird, 1989; Saetersdal *et al.,* 1993; Kershaw *et al.,* 1994; Rebelo, 1994; and see Pressey & Tully, 1994 for review). This, in turn, provides an argument for respecting the principle of complementarity in a world in which the resources available to support nature conservation are limited. We have used optimizing algorithms and heuristics for such comparisons on the Western Division data set. We found that a good heuristic identifies similar relative areas for alternative scenarios as an optimizing algorithm (Table 2(a)). It can do this with a single run. The results from 100 runs to allow for random choices in the final rule are virtually identical (Table 2(b)). The results of a bad heuristic are less similar to that of the optimizing algorithm (Table 2(a)) and can indicate widely different trends between individual runs, including large negative differences (Table 2(b)). The message from these analyses is that an intelligently written heuristic can be as valuable as an optimizing algorithm for comparative purposes, depending on how much precision is needed in the comparison. If there is a demonstrated need for very precise comparative figures then the additional time required to formulate and run optimizing algorithms might be warranted; but this is not feasible for many of the more complex real-world problems for which optimizing algorithms are intractable. It is worth noting here that there are limitations on the ability of suboptimal heuristics to compare scenarios that differ in only one or very few sites. In such comparisons, differences in the required total area of sites to achieve the representation goal are less clearly related to the differences in starting situations. When this is a problem, there are simple alternative approaches to assessing the relative contribution of sites to full representation that do not require algorithms at all (Pressey & Tully, 1994).

Comparative value of alternative algorithms in the full planning context

Representing natural features in a set of reserves is one of the goals of conservation planning. There are other important goals that make the most efficient solution to representation untenable, including maximizing the proximity or adjacency of selected sites, minimizing cost, and avoiding sites in poor condition. These goals, when combined with the representation of natural features, often require some efficiency of representation to be sacrificed (e.g. Lewis *et al.,* 1991; Bedward *et al.,* 1992; Nicholls & Margules, 1993; Lombard *et aL,* 1995) although the extent of this loss, like suboptimality, appears to be data-dependent (Freitag *et al.,* in press; Willis *et aL,* 1996). Departures from an initial set of selected sites will also be necessary as data and opportunities for protection change in the time between the initial plan and the establishment of the entire network of reserves. Extreme responses to such problems would be, on the one hand, to continue to strive for the optimal set regardless of difficulties or, on the other hand, to forget about optimality altogether and protect whatever sites become available for protection. A desirable middle course is to make judicious departures from the initial plan by minimizing the losses of efficiency necessary to secure alternative sites.

Both multiple goals and controlled departures from initial plans can be handled by optimizing algorithms (Cocks & Baird, 1989; Saetersdal *et al.,* 1993; Possingham *et aL,* 1993; Underhill, 1994; Camm *et al.,* 1996; Church *et al.,* 1996) and other algorithmic approaches (e.g. Lewis *et al.,* 1991; Nicholls & Margules, 1993). The analyses can find new optimal (or near-optimal) solutions given new sets of specified constraints relating to contiguity of sites, availability for protection, and many other factors. In situations where the constraints on implementation change through time, the analyses can be reapplied, taking into account the sites that are already part of the established network. One could argue that a guaranteed optimal solution is still desirable, no matter how many additional goals are combined with the representation of features. It is an open question, though, how much practical difference might be made by an optimal compared to a slightly suboptimal analysis when they are both applied to complex problems and made to respond to all the necessary real-world compromises. In any case, some risk of suboptimality has to be accepted for the many important problems that are intractable for optimizing algorithms, either because of time constraints or other causes of failure.

Table 2. Total areas (km 2) of pastoral holdings selected by three algorithms to represent all land types in the Western Division of New South Wales at least once; scenario 1: no existing reserves, all selections from the algorithm; scenario 2: starting with initial parts of existing reserves, before consolidation with adjacent areas (17 pastoral holdings); scenario 3: starting with all existing reserves (41 holdings); scenario 4: starting with all existing reserves plus all reserve proposals (135 holdings)

Note that the results for scenario 1 differ from those in Table 1 because the data set for this table had to be altered to take into account the boundaries of all existing and proposed reserves. [a]Areas (average of 100 runs for heuristics) for each scenario and percentage increases (bracketed) relative to the previous scenario

Algorithm	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Branch and bound (optimal)	9114	11,900 (30·6)	16,333 (37·3)	37,115 (127·2)
'Good' heuristic	10,354	12,752 (22·5)	18,030 (41·4)	44,208 (145·2)
'Bad' heuristic	15,895	18,788 (18·6)	23,524 (17·9)	45,863 (82·8)

b. Minimum and maximum percentage increases in required reserve area between reservation scenarios from 100 runs of two heuristic algorithms compared to optimal comparative results

Algorithm		1-2	2-3	3-4
Branch and bound (optimal)		30·6	37·3	127·2
'Good' heuristic	min	22·5	41·3	145·1
	max	23·2	41·5	145·2
'Bad' heuristic	min	−12·3	−9·1	61·1
	max	62·8	51·5	103·1

An alternative approach for dealing with multiple goals and controlled departures from initial selections is for planners to make the departures from efficiency themselves with an interactive system. This type of approach can start with an algorithmic solution to a representation goal (Bedward *et al.,* 1992). The initial selections can then be progressively altered, for example to increase contiguity or avoid sites in poor condition, while keeping track of representation goals and the contribution of alternative sites to achieving them. Another interactive approach is for the user to make all the selections in a stepwise manner, with representation goals and the potential contribution of sites updated at each step (Williams *et aL,* 1991; Pressey *et al.,* 1995).

We know of no trials that have compared the results of interactive systems and fully automated algorithmic solutions for achieving complex goals. Interactive systems have at least two potential advantages, though. First, the trade-offs between efficiency and other goals are not forced to proceed in the same sequence with the same relative weighting in all parts of the region and at all times. Decision-making can be flexible in time and space and the reasons for each selection can be logged for later appraisal. Second, the consequences of changing one or a few component sites of a whole network can be understood quickly and clearly. For example, an unavailable site can be excluded from the network and potential replacement sites, along with all their characteristics and locations, can be displayed in a few seconds.

Losses of efficiency due to decisions by the user of an interactive system can be displayed relative to a benchmark figure of required reserve area. The benchmark could be for representation only, with which to gauge the cost of adjustments for design and land suitability; or it could be for multiple initial goals to show the cost of changes during the vagaries of implementation. These benchmarks can also be updated each time a site is selected and so progressively demonstrate the most efficient subsequent selection. It is worth considering whether such benchmarks need to be optimal solutions or whether slightly suboptimal ones will suffice. The need for optimal benchmarks depends on the types of comparisons being made and will often be questionable given the comparative results in Table 2. The feasibility of optimal benchmarks is questionable given the intractability of optimizing algorithms for many problems and the greater speed and convenience of heuristics as parts of interactive systems.

The need to rank priorities for protection

Optimality has also been discussed in relation to the priorities of selected sites for protection. We agree with Underhill (1994) that the order in which sites are selected by a heuristic is not necessarily a reliable guide to their priority for protection. However, our reasons concern the practicalities of conservation planning more than the importance of 'ranking of priorities within optimal sets' based on a 'theoretically sound technique'. Underhill (1994) suggested that the appropriateness of a priority sequence for protection hinged on whether or not the algorithm was optimal. Yet there are at least three reasons why the selection sequence from any algorithm could bear no relationship to the 'right' sequence of acquisition and could, in fact, be dangerously misleading.

One reason is that a selected set will, for many regions, be only one of many ways of constructing a representative reserve network. Flexibility in reserve networks, due to the possibility of replacing some sites with others (Pressey *et al.*, 1994) can be explored by several approaches, including optimizing algorithms (Possingham *et al.,* 1993; Saetersdal *et al.,* 1993; Underhill, 1994; Camm *et al.,* 1996; Church *et al.,* 1996; Csuti *et al.,* in press) and heuristics (Margules *et al.,* 1991; Rebelo & Siegfried, 1990, 1992). In this context, selection of a site by one run of an algorithm can indicate little about its conservation 'value' or potential contribution to a fully representative reserve network. Many selected sites are not inherently more valuable than unselected sites and might be exchanged for them with little cost in efficiency. This potential for replacement of sites as members of future reserve networks is increased if protection is possible for more than the minimum number or total area of sites needed to achieve the representation goal.

A second, related reason for the selection order from any algorithm to have a tenuous relationship with on-ground priorities is the inevitable need for changes to selections during implementation. If complementarity is to be achieved as fully as possible, then a change in one or two selected sites, perhaps because of changes in availability for protection, will alter the set of remaining sites that best complement them (Saetersdal *et al.*, 1993). This can also be handled by progressive applications of optimizing and heuristic algorithms but indicates that an initial optimal solution is unlikely to be the most appropriate in the end.

A third reason for caution in interpreting the selection order of an algorithm as the preferred order of acquisition concerns the vulnerability of sites or their need for protection. The discussion so far has been dominated by considerations of representation. This assumes that all features in a region are equally in need of protection, an assumption that is often demonstrably wrong (Pressey, 1995). The most appropriate order of protection on the ground might be the one that protects the most threatened sites or features first or that pre-empts the imminent destruction of areas predisposed to clearing, so that maximum options for achieving a representative reserve network are open 5 or 10 years hence.

Optimal representation requires that if only a subset of a fully representative network of sites can be protected, then the best subset to protect is the one that contains the most features (Underhill, 1994). This approach can inform decision-makers about how many species can be reserved with a given input of conservation resources (Camm *et al.*, 1996; Church *et al.,* 1996) but might, in the end, facilitate the same sort of political point-scoring that measures progress in conservation by the number of hectares reserved in a term of office. A more realistic approach would be to allocate limited conservation resources to protect the features that most need protection. Otherwise, at least a part of the diversity that has been optimally selected for protection might not need it, at least in the short term. Worse, some of the features badly in need of protection might not be included in the mathematically optimal subset of sites.

For the same reasons, the optimal rate of accumulation of species as more sites are added to a notional network does not necessarily indicate the best sequence of protection. This approach assumes that the role of a reserve network is to 'save' as many features as possible as quickly as possible by representing samples of them. Another interpretation is that a reserve network is meant to facilitate the persistence of features in the landscape. Some of those features will not necessarily need the sort of protection that reserves can offer, or not in the short to medium-term, but some will need it very badly. The two interpretations of the role of reserves can lead to different priorities for protection and to different definitions of optimality. Heuristic analyses have shown that a selection order for cumulative richness can vary markedly from one that takes rarity (as one indicator of vulnerability) into account (Kershaw *et al.,* 1994, 1995). Possingham *et al.* (1993) found the same when they used stochastic dynamic programming (an optimizing method) to take into account varying risks of site destruction. Techniques for combining representativeness with vulnerability in selection procedures are therefore available but still developing. They are untested in terms of their relative effectiveness in maximizing the number of features that persist in a landscape where those features decline or become extinct at different rates.

Conclusions

In the light of these issues, what are the implications of optimality of algorithms for conservation planning? Several main points emerge from our discussion:

(1) optimal solutions to simple representation problems, as well as to more complex ones, must always be preferred to suboptimal ones but are not always feasible, either because of the required processing time or because optimizing algorithms fail to find solutions;

(2) heuristic methods are essential for the types of problems, including some important reservation goals, for which optimality cannot yet be guaranteed; with improvements in software and hardware, there will be an increase in the variety of conservation planning problems that can be solved with optimizing methods and a corresponding decrease in the reliance on heuristic approaches;

(3) the slight suboptimality of good heuristic methods comes with a substantial compensatory advantage in processing speed for large regional data sets; in some situations, and particularly for real-time decision support systems, this time difference can preclude the use of the optimizing algorithms presently available;

(4) slight suboptimality of good heuristics is not necessarily a problem when the criteria are broadened from mathematical to practical; good heuristics can be reliable comparative tools and it is not known to what extent mathematical optimality actually makes a difference on the ground after all the vagaries of implementation have been worked through;

(5) a preoccupation with optimal progressive representation of natural features can shift acquisition priorities away from the sites and features most in need of protection; in this context the term 'optimal' must be broadened to refer, not only to representation, but also to the persistence of features in the landscape, whether or not they are reserved;

(6) the quest for optimality is an enticing one but is only worthwhile if there are real benefits for conservation planning; these cannot be demonstrated by comparisons of algorithms in solving simple problems with small data sets; more imaginative comparisons in practical, rather than analytical, situations are necessary;

(7) heuristic and optimizing methods are not opposing approaches; optimizing algorithms are by no means the only promising line of development in reserve selection algorithms; the two approaches have complementary strengths and limitations and both, therefore, need further refinement as tools in conservation planning.

Progress in conservation planning will certainly depend to some extent on biologists learning techniques from mathematicians, as Underhill (1994) suggested. Conservation planning is, however, much more than the outputs of software packages. New and better algorithms are only a minor part of the progress that needs to be made in conservation planning. Major progress requires biologists as well as mathematicians to learn more about the challenges of implementing the results of algorithms in the real world.

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