

Reserve Selection Algorithms: How important is spatial accuracy?

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ABSTRACT

Reserve selection algorithms have been developed as decision making tools to aid in the conservation of biodiversity. While many researchers have developed algorithms to deal with different conservation scenarios, few explicitly deal with the accuracy of the data used. This paper explores some existing algorithms and discusses issues associated with data accuracy. Potential approaches to dealing with spatial inaccuracy in reserve selection algorithms are briefly discussed, with a view to developing future research in this area.

Keywords and phrases: reserve selection, spatial accuracy

1.0 INTRODUCTION

Reserve selection is the process of selecting areas of land that are of importance or significance for conservation given a set of criteria and objectives. Reserves may be selected to protect biodiversity, or for the direct conservation of a single or multiple species.

Reserve selection contributes towards biodiversity conservation and can help guard against habitat degradation and overexploitation (Nicholson *et al.*, 2006). As a result other benefits are often seen, such as the protection of water supplies and cultural values.

In the past, the selection of reserves has often been the result of ad hoc decisions based on many factors other than the need to represent a species or an environment system (Pressey *et al.*, 1994). Many areas that are now thought of as conservation reserves were not originally selected to preserve biodiversity, often simply being located in places unsuitable for agricultural or urban purposes (Possingham *et al.*, 2000).

Research on reserve selection has contributed a number of algorithms and tools to assist in this process in a more consistent way (see for example Pressey *et al.*, 1997; Possingham *et al.*, 2000). Some of these approaches are discussed below. This paper seeks to identify potential issues in the development and application of these approaches, and in particular argues a case for research into spatial accuracy in reserve selection algorithms.

2.0 RESERVE SELECTION ALGORITHMS

Algorithms for reserve selection include richness algorithms, rarity algorithms, a mix between rarity and richness, and, more recently, artificial intelligence methods such as simulated annealing.

Richness algorithms look at sites with unreserved features, that is, sites with features that do not already currently exist in the reserve network. The site with the most unreserved features is selected first. The algorithm then continues to add sites one at a time based on those remaining that have greatest number of reserved features. (Pressey *et al.*, 1997). In comparison, rarity algorithms look at sites containing unique features. This process continually adds sites one at a time beginning with the site that contains the rarest unrepresented feature (Pressey *et al.*, 1997).

Simulated annealing initially generates a random reserve system and then iteratively makes random changes to the selected system by either adding a new site to the system or deleting an already selected site from the system. Each new solution is evaluated against the previous solution and the best solution is kept, potentially avoiding becoming trapped in local optima (Possingham *et al.*, 2000). Nicholson *et al.* (2006) also apply simulated annealing but rather than considering only species richness or population processes, they aim to maximise persistence across multiple species.

Many of these algorithms have been implemented as reserve selection software tools. One such tool is MARXAN, a marine reserve selection tool and its predecessor SPEXAN (Ball and Possingham, 2000). MARXAN uses simulated annealing to select a series of sites that are connected spatially and that meet set biodiversity targets, given reasonably uniform species, habitat and biodiversity data.

In order to make MARXAN more accessible to users, it has been incorporated into spatial GUI environments. These include P.A.N.D.A. (Riolo, 2005), a stand-alone application that interacts with both MARXAN and ArcGIS, and CLUZ (Smith, 2004) an ArcView interface for MARXAN.

3.0 POTENTIAL ISSUES

Accuracy is an issue for any modelling situation. Inaccuracy is a form of uncertainty, and may result from lack of information and also from vagueness, randomness, heterogeneity and, in spatial contexts, from spatial dependence inherent in much geographical information (Zhang and Goodchild, 2002).

Spatial accuracy, in particular, is an issue which is perhaps not given enough consideration in reserve selection research, where data can be missing or incomplete, biased due to collection methods and processes or incompatible with other data due to collection at different scales or time periods.

Reserve selection algorithms must be both sophisticated and robust enough to deal with the challenges of varying scenarios and data quality (Prendergast *et al.*, 1999). Over the years, reserve selection algorithms have continued to advance and improve, however in many instances the data required for these models has not.

Some researchers (e.g. Cabeza and Moilanen, 2001; Prendergast *et al.*, 1999) argue that reserve design tools are of little use without high quality data. Approaches to overcome the problem of incomplete data include the use of data interpolation methods to approximate the distribution of species (Cabeza and Moilanen, 2001) and the extension of, surveys to minimise bias (Prendergast *et al.*, 1999).

However, it can be argued that all data is imperfect and contains biases and inaccuracies. Rather than looking for ways to improve data, an alternative approach is to accept that it is flawed and build algorithms that are able to extract the “maximum value” from the available data, regardless of quality (Pressey and Cowling, 2001). As the algorithm is only part of the entire process of reserve selection, other information and processes (such as expert knowledge and planning strategies) can be used to minimise the impact of potentially inaccurate data on the decision making process (Pressey and Cowling, 2001).

Gaston and Rodrigues (2003) assessed how the intensity of the sampling method affects complementary reserve selection. They found that useful results were still obtained in regions with sparse biological data. This is an important aspect of data quality but does not address the specific issue of accuracy.

In the real world, it is clearly impossible to remove all inaccuracies associated with the modelling process. However, from the brief literature review above, it appears that researchers are doing little more than recognising this as an issue. We argue that methods exist which could be incorporated into reserve selection models to explicitly recognise and deal with uncertainties, in particular spatial inaccuracy. These could include fuzzy methods to explicitly recognise data inaccuracies (Zadeh, 1965), statistical methods to deal with gaps in data (e.g. Schafer, 1997) and possibly artificial intelligence techniques such as agent based modelling to identify patterns associated with inaccurate data (e.g., Reynolds, 1987).

4.0 CONCLUSIONS

Reserve selection models can be useful decision support tools. Whilst research has continued to improve and refine reserve selection algorithms, much less emphasis has been placed on dealing with issues surrounding the quality of data employed in these models.

This discussion has highlighted areas of interest for further research. Data accuracy in spatial models such as reserve selection is an issue that, while acknowledged, is rarely dealt with explicitly. Further investigation is needed to consider the viability of addressing and dealing with issues of accuracy in these contexts.

REFERENCES

- Ball I. and H. Possingham (2000) MARXAN (v1.8.2): Marine reserve design using spatially explicit annealing, a manual, accessed 25 October 2006, <<http://www.ecology.uq.edu.au/index.html?page=27710&pid=20497>>
- Cabeza M. and A. Moilanen (2001) Design of reserve networks and the persistence of biodiversity, *Trends in ecology & evolution*, 18:5, pp. 242-248.
- Gaston K. and A. Rodrigues (2003) Reserve selection in regions with poor biological data, *Conservation Biology*, 17:1, pp.181-195.
- Nicholson E., M. Westphal, K. Frank, W. Rochester, R. Pressey, D. Lindenmayer and H. Possingham (2006) A new method for conservation planning for the persistence of multiple species, *Ecology Letters*, 9 pp. 1049-1060.
- Possingham H., I. Ball and S. Andelman (2000) Mathematical methods for identifying representative reserve networks. In: Ferson S. and M. Burgman (eds.) *Quantitative methods for conservation biology*, Springer Verlag, New York, pp/ 291-305.
- Prendergast J., R. Quinn and J. Lawton (1999) The gaps between theory and practice in selecting nature reserves, *Conservation Biology*, 13:3, pp 484-492.
- Pressey R. and R. Cowling (2001) Reserve selection algorithms and the real world, *Conservation Biology*, 15:1 pp.275-277.
- Pressey R. and I. Johnson and P. Wilson (1994) Shades of irreplaceability; towards a measure of the contribution of sites to a reservation goal, *Biodiversity and Conservation*, 3, pp. 242-262.
- Pressey R., H. Possingham and J. Day (1997) Effectiveness of alternative heuristic algorithms for identifying indicative minimum requirements for conservation reserves, *Biological Conservation*, 80, pp. 207-219.
- Reynolds C. (1987) Flocks, herds and schools; a distributed behavioural model, *Computer graphics*, 21:4, pp. 25-35.
- Riolo F. (2005) Protected areas network design application for ArcGIS, accessed 25 October 2006, <http://www.mappamondogis.it/panda_en.htm>
- Schafer J. (1997) *Analysis of incomplete multivariate data*, Chapman and Hall, London, 430pp.
- Smith R. (2004) *Conservation land use zoning (CLUZ) software*, Durrell Institute of Conservation and Ecology, Canterbury, UK, accessed 25 October 2006, <<http://www.mosaic-conservation.org/cluz/>>
- Zadeh L. (1965) Fuzzy sets, *Information control*, 8, pp. 338-353.
- Zhang, J. and M. Goodchild (2002) *Uncertainty in Geographical Information*, Taylor and Francis, London, 266 pp.