JYVÄSKYLÄ LICENTIATE THESES IN COMPUTING
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Antti Tanskanen

On optimization in reserve selection

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ABSTRACT

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Finnish summary

Reserves are needed to protect species and habitats from human activities like agriculture, forestry and building. This thesis gives a short introduction to the history of reserve selection from ad hoc decisions to modern spatial optimization methods. Basic problem settings and formulations of associated optimization problems are discussed and the data used in reserve selection is briefly introduced. Two widely used optimization methods in reserve selection are shortly described, namely heuristic optimization and linear and mixed integer programming. This thesis consists of three journal articles where two new heuristic methods for reserve selection are introduced, the greedy drop method (article I) and the greedy spatial optimizer (articles II and III). The greedy drop method removes potential reserves from the candidate reserve set according to their quality against to the remaining set. The greedy spatial optimizer adds reserves to the network according the quality of the candidate reserve and how it supports the spatial targets set to the reserve network. The usability of the new methods is demonstrated with real cases.

Keywords: spatial optimization, reserve selection, heuristics

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The story of this thesis dates back to mid 1990's. I worked together with Pertti Ranta from Metsätähti company in some vegetation mapping projects in the Greater Helsinki region. He introduced to me the idea of optimization in reserve selection and one of the fruits of this cooperation is found in I . I also thank Jari Niemelä and Arto Kurtto for making this first article possible. In Metsätähti company worked also Mikko and Paula Siitonen and cooperation with them led to new cases for optimization and also development of GSO. The first ideas of GSO was developed during dark evenings under African sky in Maputo while we prepared article I. While working together with Paula, Antti Lehtinen joined our work and took care of GIS calculations and spatial visualization. The fruits of these projects are (II,III) among others.

I'm also thankful to Antti Halkka who read an earlier version of this thesis. Pekka Punttila helped me many times catching literature and reading an earlier version of this thesis. Annamaija Lehvo read the final version of this thesis and gave valuable comments. Special thanks to Jouko Lönnquist and National Public Health Institute (NPHI) for excellent library services and good working environment. NPHI is the base for medical studies I'm involved and those projects have greatly influenced my investigations. I was kindly guided to more exact and readable presentation by my supervisor Kaisa Miettinen and thanks for her patience to read several versions of this thesis. Risto Aalto made the drawings for frontpage and cover pages of the original articles. Thanks to Annukka Seppälä for helping with cross-check of citations and understanding my always flexible timetables. My son Sakari has accepted the chaos of papers in our flat for a long time. Cooperation with people in Metsähallitus, Stora-Enso and UPM has made these articles and this thesis possible. There are still many people not mentioned here, that have had influence in this learning process in many ways. This work was financially supported by the Ellen and Artturi Nyyssönen foundation and COMAS graduate school at the University of Jyväskylä.

Helsinki, September 2005
Antti Tanskanen

LIST OF FIGURES

CONTENTS

LIST OF INCLUDED PAPERS

I Ranta, P., Tanskanen, A., Niemelä, J., Kurtto, A. 1999. Selection of Islands for Conservation in the Urban Archipelago of Helsinki, Finland, Conservation Biology, 13, 1293-1300.

II Siitonen, P., Tanskanen, A., Lehtinen, A. 2002. Method for Selection of Old-Forest Reserves, Conservation Biology, 16, 1398-1408.

III Siitonen, P., Tanskanen, A., Lehtinen, A. 2003. Selecting forest reserves with a multiobjective spatial algorithm, Environmental Science & Policy, 6, 301-309.

These are referred by their Roman numerals in the text.

1 INTRODUCTION

Reserves are needed to protect species and habitats from human activities like agriculture, forestry and building. The rate of habitat loss and species extinction is increasing and is estimated to be 100 times higher than a natural rate (Pimm and Lawton 1998).

The aim of reserves is to ensure the long-term persistence of biological diversity (biodiversity, see Haila and Kouki 1994), i.e. species, habitats and genetic diversity (Frankel and Soulé 1981). These reserve selection goals to protect species and habitats are connected to each other and in reserve selection different levels of biological hierarchy should be taken into account. In this context reserve network is a set of reserves, which are established to protect given biotic and abiotic features. The scale of reserve network design can vary from local (see Bedward et al. 1991, Rebelo and Siegried 1992, Ryti 1992, Saetersdal et al. 1993, Church et al. 1996, Lombard et al. 1997, Nantel et al.1998, Moilanen and Cabeza 2002, Erasmus et al. 1999 studies effect of the scale) to global (see Ackery and Vane-Wright 1984, Balmford and Long1995, Pimm and Lawton 1998, Andelman and Willig 2003) and features from single species (see Moilanen and Cabeza 2002) to large biotas like old-growth forest in boreal forests (II, III). Margules and Usher (1981) list several criteria for selecting reserves: (bio)diversity, rarity, naturalness, area and the threat of human interference.

1.1 Development of reserve selection

Protection of habitats in reserves is a recent phenomenon. First reserves were founded 140 years ago. Until recently, the selection of reserves was in many cases based on scenic beauty, land availability and low land prices. Decisions were made Ad Hoc without systematic planning of reserve networks. Most reserves were located on remote areas (see Pressey 1994, Margules et al. 2002) and thus species and habitats suffering from human exploitation were not properly protected. However, Kerr (1995) showed that the number of threatened bird and mammal species is strongly related to human population density. Major threats to biodiversity are human-made habitat alteration and introduced species (see Noss 2000).

It is not possible to protect all biologically important areas with given limited resources and various political preferences. Therefore, it is important to choose efficiently new areas for reserve networks (see Rodrigues et al. 1999). Development of reserve selection is described in Jongman 1995, Vuorisalo and Laihonen 2000, and Kingsland 2002.

In the following we will briefly discuss the history of the methods reserve selection has used.

1.1.1 Scoring methods

Systematic reserve selection used first scoring methods, where decisions whether to include reserve candidates into the reserve network, were made according the conservation value of candidate areas. Scoring methods use indices (see Götmark et al. 1986, Rebelo and Siegfried 1992, Turpie 1995, Andreasen et al. 2001). Indices are usually based on number of species or population sizes. Rare and threatened species are often classified as more important for conservation than common species and thus they have higher weights in index calculations (Gaston 1994, Coates and Atkins 2001). Areas having best ranks are chosen to complete a reserve network (Bedward et al. 1991). Many indices are implicitly based on the idea of nested species assemblages, where species-rich areas contain also species of species-poor areas and rare species occur mainly in species-rich areas (Wright and Reeves 1992, Atmar and Patterson 1993, Cutler 1991, 1994, Worthen 1996). Nestedness can be found in some special environments like islands (Ryti and Gilpin 1987, I), but it should be used with caution in reserve selection because frequency distributions of species and their positions in nested hierarchy varies from area to area (Saetersdal et al. 2005). Nestedness of species assemblages means that rare species are often found only in larger habitat patches. Thus single reserves must be large enough to hold these species (Berglund and Jonsson 2003, I).

1.1.2 First heuristic methods

Scoring methods consider each potential reserve candidate separately. Two areas considered valuable may contain same species or common other values, and thus they are redundant. Building reserve networks may become very inefficient when the same attributes are represented several times while others are missing. Thus usefulness of scoring methods alone is questionable (Järvinen 1985, Götmark et al. 1986). To overcome this problem biologists working with conservation problems developed greedy heuristic optimization methods in the 1980's (Kirkpatrick 1983, Ackery and Vane-Wright 1984, Margules et al. 1988, Pressey and Nicholls1989a, 1989b). These methods are based on complementarity, which means that the reserve network should represent all targeted attributes at given levels although single reserves may be less valuable (Pressey et al. 1993). Efficiency (sensu Pressey and Nicholls 1989a) of heuristic optimization methods is better than that of scoring methods (Bedward et al. 1992, Pressey and Nicholls 1989a, Turpie 1995, Williams et al. 1996). Jackson et al. (2004) showed that networks selected on complementary basis preserve better biological values than networks selected by scoring methods.

Greedy heuristic methods add areas to a reserve network one by one until they find a solution that satisfies goals and restrictions set by conservation planners. The selection is based on simple rules like select area having most unrepresented attributes (species, habitats etc.) or select the area having rarest unrepresented attributes. In a case of a tie (two or more of the candidate areas are equally valuable) additional rules are used to select among reserves. Such a rule could be: select reserve having the highest number of species. Only one rule at a time is used like in lexicographic ordering (Miettinen 1999). Greedy heuristic methods have been popular among conservationists. Heuristic methods are defined in Silver (2004): “ The term heuristic means a method which, on the basis of experience or judgement, seems likely to yield a reasonable solution to a problem, but which cannot be guaranteed to produce the mathematically optimal solution.” Thus, heuristic methods cannot guarantee optimality. In several studies heuristics have been found to produce results 2-10% poorer than optimal solutions found using linear programming (LP) methods (Pressey et al. 1996, 1997, 1999, Csuti et al. 1997), but single comparisons may not be generalized (see Rardin and Uzsoy 2001).

1.1.3 Linear programming and mixed integer programming

Linear programming (LP) and mixed integer programming (MIP) methods have been used for reserve selection much less than heuristic methods. Biologist do not know how LP/MIP methods work and they have to use these methods as a black box. The objective in a reserve selection problem is to minimize area or cost of the reserve network subject to some predefined requirements, that are the constraints of the reserve selection problem. In reserve selection each candidate area is either selected or left completely out, no partial selection is accepted. Thus decision variables have 0-1 binary values. Constraints are species occurrences or minimum population sizes, minimum areas of habitats or other biological values. Typically constraints have lower bounds and there are no upper bounds for a feasible solution. Two examples of typical constraints are: the reserve network has to contain at least 50 pairs of species i or at least 50% of the springs in the specified area have to be protected. Binary decision variables lead to integer programming (IP) problems. Many solvers use branch and bound methods (Mitchell 2001a) to solve IP problems but large problems with hundreds of constraints were not yet solvable in 1990's (Pressey et al. 1997). Larger problems are solvable nowadays with increasing computer capacity and better algorithms (Moore et al. 2003), but size limits still exists and the size limits also restrict the selection of solution methods.

1.2 Aims of the study

This study describes shortly the history and evolution of the reserve selection. The review of literature is limited to articles published in international biological literature. Some articles of the issue have also been published in operations research journals and they are considered here as well. Most optimization articles in forest research journals consider wood production and harvest scheduling optimization, an interesting optimization task, that is out of the scope of this thesis. Anyhow, some optimization examples in forest research journals have had ecological constraints or objective functions. We have included some examples here.

Secondly we introduce a new variant of heuristic optimization method described in (I), a method that removes candidate areas from reserve network until restrictions are violated. This heuristic optimization method was tested with the Helsinki archipelago reserve selection problem. In (II) and (III) we introduce a new spatial heuristic algorithm that integrates spatial calculations into a greedy heuristic algorithm. This integration makes it possible to handle spatial objectives equally to non-spatial objectives. The reserve selection problem is a spatial optimization problem and, hence, this integration removes the unnecessary restrictions of using spatial objectives in the problem design. This thesis describes the background and operation of new heuristics. The examples of using new methods are found in I, II and III and are not repeated here.

2 RESERVE SELECTION

This chapter introduces the basics of defining the goals for reserve selection of species and ecosystem protection. Issues such as data types and selection units are also briefly described.

2.1 Species protection

Many reserve selection practices have worked on a single species. These species are often threatened large vertebrates such as birds which are better known to large audience and, consequently, the protection gets easily publicity (Diamond 1986). The goal of (single) species protection is to ensure long-term persistence of viable populations (see Gilpin and Soulé 1986, Virolainen et al. 1999, Rodrigues et al. 2000b, Cabeza and Moilanen 2003). This task may include selection of areas covering productive present populations (source populations) (Winston and Angermeier 1995) and potential habitat patches (Cabeza and Moilanen 2001, Cox and Engstrom 2001, Moilanen and Cabeza 2002). For a few species requirements of habitat quality, size and location or spatial variation of vital rates in different environments are known fairly well, but for most species these are only qualified guesses (Coulson et al. 2001, With and King 2001, Araújo et al. 2002).

Species have been classified in several categories based on how threatened they are, globally (IUCN 1994, 1996) or locally (Rassi et al. 2001 for Finland). These threatened species should be targets of protection (Burgman et al. 1999, Colyvan et al. 1999, Rodrigues et al. 2000a). Different conservation scenarios can be tested from population survival perspective with tools like ALEX (Possingham and Davies 1995), RAMAS or VORTEX (Lindenmayer et al. 1995). These tools simulate populations over time and calculate extinction probabilities.

2.2 Ecosystem protection

Species distribution and abundances are seldom available for larger areas. In practice distribution is possibly known only for some taxa such as birds. Thus, many times a practical conservation decision has to rely on the distribution of ecosystems or land classes (McKenzie et al. 1989, Nicholls 1989, Faith and Walker 1996, Pressey et al. 1997, Pressey and Logan 1998) or combining species protection with environmental protection (Fairbanks et al. 2001, Lindenmayer et al. 2002). Detailed information being unavailable, reserve selection based on land classes is better than arbitrary placement of reserves, especially when combined with distribution data of species (Pressey and Logan 1995). For example in Finland mires are divided into several classes, each class having typical plant species (Eurola and Kaakinen 1978) and even a characteristic insect and bird fauna. By protecting these land classes or habitats we can at the same time protect all biota living there.

2.3 Spatial data

In reserve selection data of species, environmental variables or human activities have three major dimensions: place, time and subject.

Place can be a point, a line or an area. Place can be defined by biological attributes: place and area of a habitat, territory of an endangered bird or a point of observation. Place can be the area of a land holding or defined according to administrative boundaries. These administrative spatial definitions seldom overlap with biological boundaries.

Time is often omitted in spatial data. Data can be a snapshot sampled at one time, for example a field mapping made in one year. Reserve selection based on such a snapshot may lead to local extinctions due to temporal and spatial variation of populations (Margules et al. 1994, Virolainen et al. 1999). Many times data have been collected for other purposes during a long period of time and are drawn from registers created for those purposes. These kinds of data do not present the distribution of organisms at any given time, but merely a sample of distributions over a certain period. Species do have natural fluctuations of population sizes and distributions and the stage of the population at the time of inventories should be known (see Haila et al. 1994). Especially with endangered species it is important to include time of observations in reserve selection because distributions of species may have radically reduced during data collection.

Subject can be amounts of pairs of a species, type of land class, age of forest or type of habitat or any feature of interest. For reserve selection many background variables, such as the ownership or conservation status of an area, can be collected from administrative databases. Often species distribution data is found from museum collections, mappings or field inventories done for other purposes. In these cases data quality and completeness for reserve selection purposes must be considered (see Lombard et al. 1995 for an example). Polasky et al. (2000) use a probabilistic model for species occurrence with incomplete presence – absence data.

The restrictions of the reserve selection problems are defined by spatial data. Therefore, the spatial data available or possibility to gather data often guides the definition of the reserve selection problem and also the definition of selection units.

2.3.1 Selection units

A selection unit is a piece of land or sea which is considered to be included into the reserve network. As mentioned earlier, no partial selection is allowed. Selection units can be grid cells (for example1 km x 1 km squares), land parcels determined by ownership or areas defined according to habitat boundaries or other biological variables. Grid cells have been popular in many reserve selection exercises. They are easy to use and distances between cells, neighbourhood and boundary lengths are easy to calculate. Some biological data, e.g. bird atlases, are collected in grid cells (see Williams et al. 1996 for an example). This makes grid cells useful as selection units. One should note that borders of grid cells seldom coincide with biological boundaries and the same is true for land ownership. However, land ownership often influences on land availability for protection. Thus, it should be considered in reserve selection.

Forest patches, called stands, used by forestry are examples of land division based on biological differences. Patches are defined by soil type, dominant tree species and the age of trees. In practice, biological boundaries are better suited for reserve selection than other land divisions because conservation goals are biological. Grid cells small enough do not extend over several different habitats or other biological classification. Thus, small regular units like grid cells have advantages of simpler topology with sufficient biological accuracy.

Pressey and Logan (1998) showed advantages of smaller selection units. Optimization with smaller units resulted in less over-representation of goals and cheaper reserve networks with equal goals compared with larger selection units. On the other hand, smaller selection units make reserve selection more complicated. For example, moving from 10 km x 10 km to 100 m x 100 m grids makes the number of selection units 10^4 times larger and the problem may become too large to handle and difficult to solve.

2.3.2 Species data

Species data is based on sampling from populations. Large areas and large amounts of rare species may lead to inaccurate estimates of number of species unless very extensive expensive sampling is used (Williams 1998). Martikainen and Kouki (2003) showed that to rank not more than 10 boreal forests by threatened beetles, it is necessary to sample 10^5 beetle individuals. Such sampling effort is not possible in larger areas and, for example, in developing countries.

The advantage of using species distribution data is that (threatened) species are most often the targets of protection. In practice reserve selection is often based on occurrence data of larger animals, vegetation types or tree species (see Gaston and Rodrigues 2002). In many cases only presence observations are recorded, and recorded absences are missing. This causes difficulties in constructing species' distributions and estimating false negatives (Margules et al. 2002).

The use of surrogate (focal) species or taxonomic groups instead of complete sampling of all species of interest have given mixed results (Ryti 1992, Prendergast et al. 1993, Faith and Walker 1996, Williams et al. 1996, Noss 1999, Howard et al. 1998, Saetersdal et al. 2003, Hess et al. 2006). Saetersdal et al. (2003) showed in Norway that species richness of vascular plants of pine and deciduous forests explained species richness of seven taxa out of eight statistically significantly. This reflects similar response to certain abiotic differences including fertility, topographic position or vegetation cover. Single species seldom indicate species richness even if species composition is nested and compositions of surrogate species vary from area to area (Saetersdal et al. 2005, Chen et al. 2005). Thus the use of surrogate species should be examined a priori for every new case for example with smaller test areas.

2.3.3 Environmental data

Environmental characteristics like soil type or annual rainfall partly determine vegetation types and species composition of different taxonomic groups. Thus, environmental data can be used in reserve selection to protect species. Faith and Walker (1996) showed with a simulation example how environmental characteristics used in reserve selection can find reserve networks covering rare species not detected in field studies. Environmental data such as soil type, height or direction of slopes, rainfall, temperature or vegetation cover is usually available without field inventories. Also data of human exploitation like agriculture, roads and buildings are important for reserve selection. Especially recreation potential often depends on roads and other human-made services. However, Pearce and Ferrier (2001) showed that only a fraction of species abundances where predicted with coarse environmental variables.

Reserve selection based only on environmental data did not produce satisfactory reserve networks for mammals, birds, reptiles nor plants in a European wide study (Araújo et al. 2001). However, combining environmental data and species data often gave better results than either alone (Nantel et al. 1998, Tole 2006).

2.4 Summary

The reserve selection problem is often defined according to the limits of data available. Even if biological knowledge could allow the formulation of more complicated and advanced optimization problems, the data quality can make these optimization problems useless. The amount of uncertainty in different variables is often inter-dependent and it could be a mistake to omit this information (Kangas et al. 2005). Thus we need to fit the knowledge of biological processes and data available to build a reserve selection optimization problem.

3 OPTIMIZATION OF RESERVE SELECTION

This chapter introduces notations and definitions for reserve selection problems. Two commonly used basic problem types, as well as a general problem setting and spatial optimization problems are shortly described. Greedy heuristic methods used in reserve selection are introduced and linear programming is briefly discussed.

3.1 Why optimization?

Survival of species is strongly depending on the amount and spatial distribution of suitable habitats. Small changes of these factors may radically change probabilities of species extinction and, consequently, protection goals (amounts of habitats, sizes of populations etc.) in reserve selection should be above critical levels (Fahrig 2001). Human activities outside a reserve network can also have strong effects on species survival (Cabeza 2003) and should be taken into account while planning future conservation activities (Drechsler 2005). Pressey (1994) lists dangers of Ad Hoc reserve selection (discussed in Introduction). It is expensive, biased and inefficient (sensu Pressey and Nicholls 1989a). Thus, optimization has potential to improve species survival as compared to Ad Hoc reservation with the given limited resources available for reserve selection.

Bedward et al. (1992) give an example of a conservation design tool named CODA, where optimization is one part of the planning system. The CODA system has been used in Australia for real world conservation practices. It divides reserve selection in to several steps: Data collection and preprocessing, goal setting, preselection of areas, optimization for reserve selection, post processing of the results and adjustment of reserve network boundaries. This kind of a systematic reserve selection procedure ensures that all the steps of reserve selection are done in a sensible order. The optimization without proper data, meaningful goals and adaptation of results can yield poor results.

3.2 Problem setting

The reserve selection problem is to choose from the set of candidate selection units (areas) a subset to build a reserve network. While minimising the cost of acquiring areas the reserve network has to fulfill several quality and location criteria defined by the decision makers. The qualities of candidate selection units are described with features like habitat type or occurrence of species. Selection units cannot be partially selected. Thus, the problem is a zero-one optimization task. Each selection unit has a non-negative cost. Hence, removing any selection unit from the reserve network always keeps equal or lowers the cost and thus enhances objective function value (a minimizing problem). An alternative approach to formulate the reserve selection problem as an optimization problem is to set budget constraints and to maximize the quality of the reserve network. These are the two ways the reserve selection problem has been formulated in the literature before mid 1990's.

3.2.1 Notation

Let us assume that we have I candidate selection units, indexed by i=1, 2, ..., I, and J features, indexed by j=1, 2, ..., J. The corresponding sets are *I* and *J*, respectively. The I x J matrix **A** has elements a_{ij} which equals the amount of feature j in unit i. If we are only interested of the presence of feature j in unit i, we denote the presence with 1 and otherwise a_{ij} equals 0. The cost of acquiring a candidate selection unit i for the reserve network is c_i. Matrix **A** and costs $c_1..c_I$ are known a priori. The decision variable vector is $Y = (y_1, y_2, ..., y_I)^T$, where y_i equals 1, if the candidate selection unit i is selected and equals 0 otherwise. In addition we can form an additional vector $X = (x_1, x_2, ..., x_J)^T$, where x_j equals 1 if feature j is present in the reserve network that is to be constructed, otherwise 0.

3.2.2 Spatial definitions

We also know the following data of candidate selection units in I. The area of the candidate selection unit k is A(k). The distance between selection units k and m, denoted by $d_{k,m}$, is calculated as border to border minimum distance. The distance from candidate selection unit k to the closest already selected selection unit is $d_{k,*} = \min(d_{k,i}), i \in \{I \mid y_i=1, i \neq k\}$. The length of the perimeter of a selection unit k is L(k). The length of the common border of selection units k and m is denoted by L(k, m) if $d_{k,m} = 0$, otherwise the length is 0.

A continuous area Ca is a set of selection units that share common border(s). A continuous area can have holes; the only assumption is that any two points in Ca can be connected with a set of selection units in Ca having in pairs zero distances. In other words, k, m $\in$Ca, if there is a set of selection units {k, c1, c2, ..., cn, m}, where $d_{k,c1}=0$, $d_{c1,c2}=0$, ..., $d_{cn,m}=0$. The distance between two continuous areas denoted by Ca_k and Ca_m is defined as a distance between closest selected selection units in those spatial structures and we denote it by $d_{Cak,Cam}$. Let us denote the number and set of continuous areas in the reserve network with Nc and NC, respectively. We set $Z_{m,k}=1$, if selection unit k belongs to continuous area Ca_m, otherwise $Z_{m,k}=0$. The area of continuous area m is

$A(Ca_m) = \sum_{k=1}^{I} A(k) z_{m,k}$. The length of the perimeter of Ca_m is

$L(Ca_m) = \sum_{k=1}^{I} L(k) z_{m,k} - 2\sum_{k=1}^{I} \sum_{l=1}^{I-1} L(k,l) z_{m,k} z_{m,l}$. The latter part of equation removes those parts of common borders of the selection units in the continuous area m, that are within the continuous area m.

A cluster is a set of continuous areas so that there is a path of continuous areas between any two continuous areas in a cluster. In the path the shortest distance between any two continuous areas one after another do not exceed a predefined maximum inter-cluster distance md. Let us denote the l'th cluster with Cl_l. In other words, for any pair $Ca_i, Ca_m \in Cl_l$ there is a set $Ca_i, Ca_{i+1}, Ca_{i+2}, \ldots, Ca_{i+n}, Ca_m \in Cl_l$ so, that $d_{Cai+k,Cai+k+1} \leq$ md, k=0, ...,n. The area of cluster Cl_l is the sum of all continuous areas belonging to Cl_l. Let us denote the number and set of clusters in the reserve network with Nl and NL respectively.

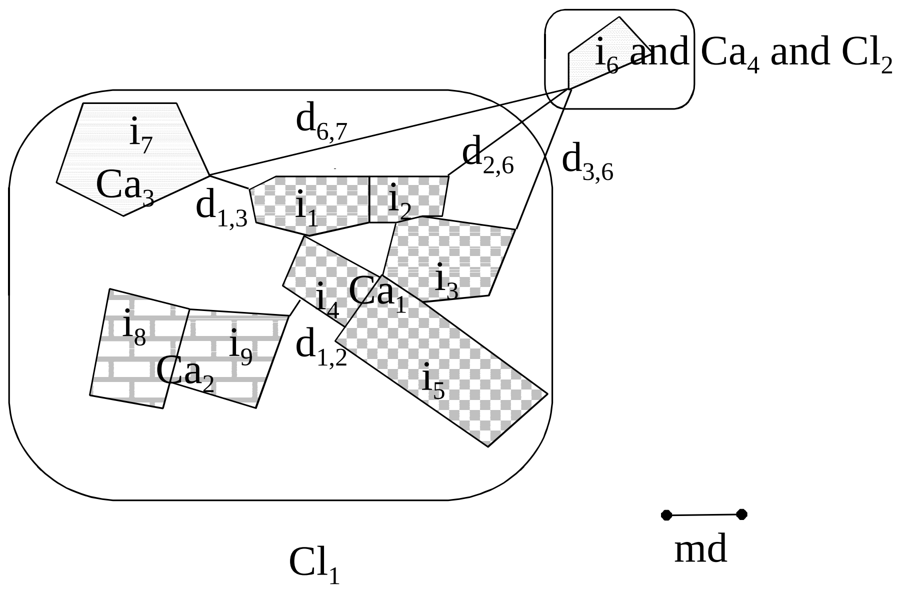

FIGURE 1 An example of selection units, continuous areas and clusters

Figure 1 shows hierarchy of spatial structures. It shows a situation, where selection units i_1, ..., i_9 are selected. Units which are not selected are not show in the figure. There are two clusters Cl_1 and Cl_2. Cl_1 consists of three continuous areas Ca_1, Ca_2 and Ca_3, because $d_{ca1,ca2}$ and $d_{ca1,ca3}$ are less than md. Cl_2 consist of one selection unit i_6. Minimum distance from i_6 to closest selected selection unit d_{6*} equals to $d_{3,6,}$. The distance between i_6 and i_3 and is longer than md, which makes i_6 a separate cluster. Unit i_6 has no common borders with any of the other selected units because $d_{6*} >0$. Thus, i_6 is also a separate continuous area Ca_4. There is a hole in the continuos area Ca_1, an area that is not selected but is surrounded by selection units in Ca_1.

In the following we present two commonly used problems types, the minimum set problem (MSP) and the maximal coverage problem (MCP). Finally, we outline a general problem setting for the reserve network selection.

3.2.3 Minimum set problem

The minimum set problem (MSP) (Church et al. 1996) minimizes the cost of a reserve network while representing each feature j (species) at least r_j times in selected areas (Underhill 1994, Pressey et al. 1997, Hamaide et al. 2006). Minimum levels $r_1, \ldots, r_J$ for features 1, ..., J are given a priori according to biological needs for a reserve network. The MSP formulation is:

$$\text{Minimize} \sum_{i=1}^{I} c_i y_i \tag{1}$$

$$\text{subject to} \sum_{i=1}^{I} a_{ij} y_i \geq r_j, \quad \text{for each } j \in J \tag{2}$$

$$\text{where } y_i = 0 \text{ or } 1 \tag{3}$$

Objective function (1) minimizes the cost of a reserve network, constraints (2) limit the feasible region in such manner, that feature (species) j is found at least r_j times in the network and constraint (3) ensures that selection units cannot be partially selected.

3.2.4 Maximal coverage problem

The formulation of a maximal coverage problem (MCP) is as follows:

$$\text{Maximize} \sum_{j=1}^{J} x_j \tag{4}$$

$$\text{subject to} \sum_{i=1}^{I} a_{ij} y_i \geq x_j, \quad \text{for each } j \in J \tag{5}$$

$$\sum_{i=1}^{I} y_i \leq p, \tag{6}$$

where $x_j = 0$ or 1, $y_i = 0$ or 1. (7)

In (MCP) the number of selected units y_i is restricted with an upper limit p (6) given a priori. The number of features x_i is maximised (4) (Church et al.1996, Csuti et al. 1997). Constraint (5) ensures that x_j=1 only if feature j is present in network and constraint (7) sets upper limit of x_j to1. Constraint (6) limits the total number of units in a reserve network to p. This is often a more realistic formulation for practical conservation work than MSP (Camm et al. 1996).

In a more general model of MCP constraint (5) is replaced by $\sum_{i=1}^{I} a_{ij}y_i \geq r_j x_j$ where feature j must occur at least a priori given r_j times in the network. MCP does not count any partial representation of features j under level r_j because x_j is zero if representations of feature j is less than r_j in the reserve network. On the other hand, also over-representation of feature j is ignored.

To change constraint (6) so that it limits the cost of selected areas to b instead of the number of areas to p, we need costs $c_1, \ldots, c_J$ of selection units 1, ..., J and constraint (6) must be replaced with

$$\sum_{i=1}^{I} c_i y_i \leq b \, .$$

An example of comparison of MSP and MCP is found in Ando et al. (1998).

3.2.5 General problem setting

The two problems, MSP and MCP represent special cases of more general goals to preserve nature. The major weaknesses of MSP and MCP are, that they do not consider interactions e.g. dispersal between chosen areas in the reserve network, they do not consider interactions between reserve networks and surroundings or the shape and spatial arrangement of the reserves. Local population sizes in reserves fluctuate and some local populations go extinct while others are established by colonization. Extinction is related to population size (or suitable area), time since fragmentation occurred and severity of fragmentation (Patterson 1990, Hanski 2000, Solé et al. 2004), whereas colonization is related to the distance from other populations (MacArthur and Wilson 1963, Diamond 1975). Population sizes in reserves may also be simply too small for long term persistence (Gilpin and Soulé 1986). The survival of species in reserves depends on what is happening outside reserves (Fahrig 2001, Cabeza and Moilanen 2003). Nantel et al. (1998) classify habitats according to their fragility to human activities and land-use potential. Costello and Polasky (2004) analyse long-term area selection, where land availability and human development risk changes over the planning horizon (often several years) and budget restrictions prevent immediate protection of all needed areas. The use of habitat destruction rates and irreplaceatibility of selection units improve the results of long term reserve selection (Pressey et al. 2004).

Optimization models differ from case to case. Goals of protection may vary as well as means of protection. Often planning is done with incomplete and sparse data. Araújo and Williams (2000) show a successful example of using sparse occurrence data of European trees together with environmental data to select areas giving increased probability of persistence for the tree species in comparison of using either data alone. This shows how data collected to other purposes can be used to target resources to right areas and how the data available affect the problem setting.

In reserve selection the objective could be to maximise biological diversity and the restrictions can be budget constraints. Objectives and constraints can be interchanged and then costs are minimised while minimum protection levels are constraints. Actually, here we have two objectives, maximization of biological diversity and minimization of the cost, and when they are considered simultaneously, we have a multiobjective optimization problem (MOP) (Rothley 1999). The two first mentioned ways can be seen as using the ε-constraint method for solving this problem (see Miettinen 1999). Rothley et al. (2004) present a MOP reserve selection problem, where they had five objectives and generated ranking order for ten best areas by each objective. The optimization problem was to include as many of these best ranked areas of each objective in a ten area reserve network. This technique uses scoring and optimization together but lacks the power of direct multiobjective optimization of objectives.

3.2.6 Spatial optimization

Reserves should be of adequate size and compact enough to minimize edge effect, which means how surroundings of reserves change microclimate, radiation and species composition at the edges of reserves (Saunders et al. 1991, Harrison and Bruna 1999, Debinski and Holt 2000, Laurance 2000). The part of reserve interior, where there is no edge effect is called core area. Metrics commonly used to describe compactness of the area, are different area - perimeter ratios and amount of core area (Siegfried et al. 1998, Clemens et al. 1999, Bogaert et al. 2000, Fitzsimmons 2003). A widely used area- perimeter ratio is $\varphi_1 = \sum_{k=1}^{Nc} A(Ca_k) / \sum_{k=1}^{Nc} L(Ca_k)$ over the set of all continuous areas NC. This ratio φ_1 is not scale invariant. A scale invariant ratio is $\varphi_2 = \sum_{k=1}^{Nc} A(Ca_k) / (\sum_{k=1}^{Nc} L(Ca_k))^2$ (Bogaert et al. 2000). Both φ_1 and φ_2 obtain their maximum values for circle shaped areas (Bogaert et al. 2000). If the intensity of edge effect inside the reserve depends only on the distance from the reserve border, circle shaped area also maximizes the proportion of core area in a reserve. Core area can be defined in various ways. An example is a grid cell, for which all neighbours belong to the reserve network (Williams and ReVelle 1998). We can also define core area so that from any point in core are the distance to the edge is more than m meters. Edge effect is strong in fragmented human dominated landscapes and should be considered in reserve selection (van Langevelde et al. 2002). In contrary to many studies Bertomeu and Romero (2001) maximize the area of edge in reserve selection to support populations of species utilising edges or several habitats such as old forest and clear cuts outside reserves for example for breeding and foraging. The scale of reserve network design often depends on administrative decisions, but spatial goals in optimization should be adjusted according to biological needs (Drechsler and Wissel 1998, Norton et al. 2000, Cox and Engstrom 2001, Jansson 2002, Larson and Sengupta 2004).

Nicholls and Margules (1993) were the first to integrate spatial characteristics to optimization of reserve selection. They used a greedy heuristic method which chose the closest area to the already selected areas from otherwise equally good candidates in case of a tie. To add new spatial rules to heuristics, such as adjacency, has been the most common way to integrate spatial targets to optimization (Nicholls and Margules 1993, Lombard et al. 1995, 1997, Freitag et al. 1997). Williams and ReVelle (1998) used a core and buffer model, where a buffer is an edge area of a reserve (inside reserve) or areas next to a reserve (outside reserve). Only species protected in core areas where counted and the cost of a reserve network was minimized. This model was further developed to a bi-objective model to maximize the number of species protected in core areas while minimizing cost of a reserve network (Clemens et al. 1999). Bevers and Hof (1999) demonstrated an opposite situation of wildlife habitat optimization, where species use edges or two or more habitat types for foraging or nesting.

However, adding spatial targets to optimization has been difficult. One way to increase compactness of a reserve network is to minimize the length of the total perimeter of a reserve network (Possingham et al. 2000, McDonnel et al. 2002). Cabeza et al. (2004) used forward and backward heuristics to minimize the total perimeter in reserve selection. All these methods are based on one or a couple of spatial functions like area-perimeter ratios that are minimized or maximized. Kurttila et al. (2001) use a combination of stand boundary lengths and boundary qualitites. Boundary quality means here the difference of neighbouring stands at opposite sides of boundary. Bunn et al. (2000) used a graph theory-based heuristic to select reserve networks for two differently dispersing animals in North Carolina, USA. Minimum spanning trees between candidate areas were calculated for both species based on their dispersal ranges. The first objective was to minimize the negative change of flux (connectivity, the potential of animals to move between areas) by removing candidate areas one by one. The second objective was to minimize the decrease of traversability, defined as change of a diameter of the largest component of the graph before and after area was removed. Thus, the method gives the relative importance of areas to species dispersal as corridors and stepping stones(see also Fuller and Sarkar 2006). Hof and Bevers (2000) optimize directly size of endangered animal populations and use four different spatial dispersal models to place reserves and management actions. Several examples of modelling connectivity in reserve network selection are given in Hof and Flather 1996 and methods of spatial optimization for forestry and conservation are given in Hof and Bevers 1998. Cova and Church (2000) present a spatial method, where global spatial problems are decomposed into smaller local problems. Snyder et al. (2004) present bi-objective weighted models to maximize representation of features and minimize area of the reserve network.

Steward et al. (2004) formulate an optimization problem for multiple land use, where reserves are competing with agriculture, forestry and other land uses. Their method aggregates different land uses into clusters to avoid fragmentation. Rothley (1999) presents a multiobjective optimization method, where all Pareto optimal solutions (see Miettinen 1999) are found at first. In his example there were three functions (max connectedness, max area and max rare plant species) to be optimized and size of an exercise was to select 5 areas out of 20. Connectedness was defined as a sum of inverse distances between selected pairs of areas $(k,m) \in IxI$, $k \neq m$, $y_k=1$, $y_m=1$, in other words $\max Z_1 = \sum_{m=1}^{I} \sum_{k=1}^{I} (1/d_{k,m})(y_k y_m)$, $d_{k,m} > 0$, where $d_{k,m}$ is the distance between areas in selected pair (k,m), I^2 is the total number of possible pairs. Problem was solved with LP solver LINDO 5.3 (LINDO Systems 1995) software and it generated 36 Pareto optimal solutions out of $\binom{20}{5}$ = 15 504 possible combinations. These 36 solutions where compared with a simple multi attribute rating technique (SMART) (Rothley 1999). Trade-off tables were calculated and they showed how the best solution depended on the weights put on each criterion. Comparing Pareto optimal solutions a posteriori in reserve selection is a well-working method because the decision maker can see solutions on maps as well as pros and cons of solutions from trade-off tables. Williams et al. (2005) give a comprehensive review of spatial optimization in reserve selection.

3.3 Optimization methods in reserve selection

In reserve selection, optimization methods used have mainly been greedy heuristics of lexicographic type (see Kirkpatrick 1983, Margules et al. 1988, Pressey and Nicholls 1989b, Bedward et al. 1992, Nicholls and Margules 1993, Pressey et al. 1993, Saetersdal et al. 1993, Willis et al. 1996, Freitag et al. 1997, Nantel et al. 1998, Fairbanks et al. 2001, Polasky et al. 2001, Reyers et al. 2002, William and Araújo 2002, Cabeza 2003, Cabeza et al. 2003, a few to mention). Linear programming has been used several times (see Willis et al. 1996, Williams and ReVelle 1998, Woodhouse et al. 2000, Bertomeu and Romero 2001, Rodriques and Gaston 2002, Rothley 2002, Bettinger et al. 2003, Memtsas 2003, Moore et al. 2003, Ruliffson et al. 2003, Diaz-Balteiro and Romero 2004, Crossman and Bryan 2006), but metaheuristics like simulated annealing

(Csuti et al. 1997, Possingham et al. 2000) and genetic algorithms (Moilanen and Cabeza 2002, Seppelt and Voinov 2003, Steward et al. 2004, Moilanen 2005) have been seldom used. The reserve selection problems have been variants of MCP and MSP with linear restrictions and mostly with a single objective function.

3.3.1 Heuristic methods

Heuristic methods seek fast solutions for optimization problems. They do not guarantee to find the optimum but they can solve problems that are very hard to solve with mathematical optimization methods. Heuristics can simulate human decision making like greedy heuristics often do or their ideas have been adopted from other fields of science like genetic algorithms (Davis 1991) or simulated annealing (Kirkpatrick et al. 1983). Bettinger et al. (2002) compared the performance of eight heuristic methods including simulated annealing, tabu search, and genetic algorithms to three increasingly difficult spatial wildlife planning problems. They found no major differences between best solutions found with different heuristics excluding random search, which gave the worst results. A recent comprehensive review of the heuristic methods is given in Silver 2004. In the following, greedy heuristic methods are presented with an example.

Greedy iterative methods add new units to the network until the reserve network fulfills all the constraints or there is no reserve network satisfying all the constraints. The role of objective functions and constraints is not always clear in descriptions of greedy methods in reserve selection. Iterative methods commonly used in reserve selection do not directly minimize cost of a reserve network. Selection rules (that is, objective functions) maximize amounts or occurrences of those biological features 1, ..., J, which still are under given levels r_j, $\sum_{i=1}^{I} a_{ij} y_i < r_j$ and thus these rules resemble the objective function used in MCP. Methods terminate, when all features J are represented in a reserve network at given levels $r_1, ..., r_j$ (2) and thus no new selection units are needed. Methods have been described as written rules in the majority of biological literature (Kirkpatrick 1983, Ackery and Vane Wright 1984, Thomas and Mallorie 1985, Margules et al.1988, Rebelo and Siegfried 1990, 1992, Nicholls and Margules 1993, Saetersdal et al. 1993, Lombard et al. 1995, Pressey and

Logan 1995, 1998, Williams et al. 1996, Freitag et al. 1997, Csuti et al. 1997, Pressey et al. 1997, 1999, Freitag and Van Jaarsveld 1998, Nantel et al. 1998, Araújo and Williams 2000, Cabeza 2003, Cabeza and Moilanen 2003). Mathematical formulation (Ryti 1992), flow charts (I, II) or pseudo code (Cabeza et al. 2004) of heuristics are seldom used. Written descriptions often omit constraints and a solution is found when all candidate selection units have zero values for all objective functions (rules) in a lexicographic maximization problem.

As an example we present here a method that Margules et al. (1988) published. It was one of the first greedy iterative lexicographic methods for reserve selection to solve MSP. This iterative method uses one objective function (rule) at a time to add new selection units to the reserve network. In case of a tie, when two or more candidate units have the same best objective function value, this method uses additional objective functions. This method has four lexicographically ordered objective functions. This means that the most important object function is the first one, the second most important is the second one etc. First all units having unique features are selected. To be more specific, the first rule is to include all selection units i having unique occurrences of target features, like species or land classes having $\sum_{i=1}^{I} a_{ij} = 1$. These selection units containing unique features must be in the reserve network to satisfy constraints (2) in MSP, because every r_j has to be positive to be a real restriction. Thus these units are selected at first.

The iterative part of the method starts by applying the second rule to select units with rarest (non selected) features and among them the area contributing largest amount of new features. This rule has two parts. The first part selects units i from unselected units having the rarest non-presented features j, in other words those having minimum number of occurrences. Let us denote this minimum with $a_{jmin} = \min_{j=1..J} \sum_{i=1}^{I} a_{ij}(1 - y_i)$. Let us denote the set of rarest features with $J_{rarest} = \{ j \in J | \min_{j=1..J} \sum_{i=1}^{I} a_{ij}(1 - y_i) = a_{jmin} \}$. The set of selection units having any of these rarest features is now $I_{rarest} = \{i \in I | a_{ij}(1 - y_i) = 1, j \in J_{rarest}\}$. If more than one selection unit belongs to I_{rarest}, the method uses a second part of the rule to select units having largest number of new features $a_{maxi} = \max_{h \in I_{rarest}} \sum_{j=1}^{J} a_{hj}(1 - x_j)$, let us denote this set by

$I_{new} = \{h \in I_{rarest} | \sum_{j=1}^{J} a_{hj}(1 - y_h) = a_{maxi}\}$. If there is more than one candidate selection unit in set I_{new}, then the method uses a third rule to select the area having a non-presented feature, in other words j having $\sum_{i=1}^{I} a_{ij}y_i < r_j$ and having the smallest sum of occurrences in unselected selection units $a_{smallest} = \min_{i \in I_{new}} \sum_{j=1}^{J} a_{ij}(\sum_{i=1}^{I} a_{ij}(1 - y_i))$. Thus the set of these selection units is $I_{least} = \{i \in I_{new} | \sum_{j=1}^{J} a_{ij}(\sum_{i=1}^{I} a_{ij}(1 - y_i)) = a_{smallest}\}$. If there is still a choice, the area from I_{least} is selected randomly. The method iterates until no candidate selection units have a feature, that is present under r_j times, j= 1, ..., J, i.e., until there exist no such i and j, that $\sum_{i=1}^{I} a_{ij}y_i < r_j$. If there is some feature j present under r_j times in the reserve network, but $\sum_{i=1}^{I} a_{ij}(1 - y_i) = 0$, there is no reserve network fulfilling all restrictions and the method terminates. Many greedy heuristic methods have been developed from this Margules et al. (1988) method by changing rules or their order. For example different rarity scores have been used as well as species richness scores as selection rules (see Pressey et al. 1997).

The advantages of greedy heuristics are easy implementation, speed and understandable logic. Heuristics can not guarantee optimality and the degree of inefficiency (sensu Pressey and Nicholls 1989a) depends on the data and decision rules used in heuristic method and it is often 0–10 percent (Church et al. 1996, Csuti et al. 1997, Pressey et al. 1997). Greedy heuristics select units according to their objective function value, and the unit having the best value is always chosen. Land acquisition can be based on this selection order.

3.3.2 Linear and mixed integer programming

Linear programming (LP) was for the first time used in reserve selection by Cocks and Baird (1989). Reserve selection problems are mixed integer programming (MIP) problems and most MIP solvers use branch and bound (B & B) methods to find optimal solutions (Achterberg et al. 2005). Other techniques are branch and cut (Mitchell 2001a, Padberg 2001), and cutting plane (Mitchell 2001b, Marchand et al. 2002), for example. To illustrate the functioning of the B & B method we use the MSP problem. Selection variables $y_1, ..., y_I$ are binary variables. Solving linear problems without integer restrictions but with restrictions $y_i \in [0,1]$ usually produces non integer y_i values between zero and one. The B & B method is based on a best - first tree search. The root node is the relaxation of original MIP problem into a LP problem without binary restrictions. In generic B&B implementations two child nodes are generated and inserted to the search tree; one with restriction y_i=0 and the other with y_i=1. The B & B method passes the search tree and keeps track of the so far best MIP solution. Solving an LP problem in a node has three possible outcomes:

1. The node is infeasible for the LP problem. This means that no search down from this node is needed. If the node is root, then there is no solution for the original MIP problem.
2. The node is optimal for the LP problem, but infeasible for MIP problem. Some restrictions $y_i \in \{0,1\}$ are violated. If the solution is better than the best found so far, it is necessary to continue search and make a branch y_k=0 and y_k=1 with some $k \in I$. Then both substrees are searched.
3. The node is optimal for the LP problem and feasible for the MIP problem. If the solution is better than best so far found, this replaces the best solution. The tree is also pruned, i.e., nodes having worse or equal solution are removed.

When the tree has fully been explored, the best found MIP solutions is also the solution of original problem (Makkonen and Lahdelma 2006).

In the worst case the whole feasible area has to be examined, and the number of branching is not know a priori. The method is sensible to the passing order of the feasible region and several methods for partitioning strategies, branching variable selection and subtree passing order selection have been developed (Lee and Mitchell 2001).

Although biologists knew, that heuristics do not always find an optimal solution (Underhill 1994), most reserve selection optimization was done in 1980's and 1990's with greedy heuristics. There were three major reasons for the predominant use of heuristics (Pressey et al. 1996, 1997). First, heuristics have often proven to give almost optimal solutions (sensu Pressey and Nicholls 1989a) (see also Willis et al. 1996, Csuti et al. 1997). Secondly LP methods are not capable to solve realistic problems of large size and complexity. The third reason is that LP methods solve problems too slowly and it takes hours or days to get a solution to the problem.

Rodrigues et al. (2000a) showed that in some cases heuristics have given solutions having objective function values up to 40% larger than the optimum, although in these cases heuristics have been used incorrectly (see Saeterdal et al. 1993). Rodrigues and Gaston (2002) also showed that a problem of a typical size with hundreds of decision variables is solvable within seconds using LP solver CPLEX (ILOG 1999), although CPLEX did take with some problems up to 29 hours with Pentium II PC to find a global optimum.

Often there are several alternative optimal solutions to MSP and MCP problems. LP methods typically find only one of these and other equally good solutions are not discovered. Arthur et al. (1997) present a method to find all optimal solutions. They defined new parameters y_{1i}, y_{2i}, ..., where the first index is the number of subsequent solution and the second index is the number of the unit. They restrict all earlier found solutions with a set of new constraints, where y_{1i}=1, i=1..I, if unit i is selected in the first solution, otherwise y_i=0. Then a new constraint $\sum_{i=1}^{I} y_{1i} \leq p-1$ is used for MCP formulation together with (5). The constraint limits new solutions to contain at most p-1 units from the first (previous) solution. New parameters y_{2i}, y_{3i}, ... are added as long as new equally good solutions are found. Often these equally good solutions consist of almost equal sets of units. There may be a set of units, that are in every solution. They are called irreplaceable. Irreplaceability, how some units in a reserve network can not be replaced by others, depends on the number of different solutions and the sets containing particular units. This problem is studied in detail by Ferrier et al. (2000), see alsoTsuji and Tsubaki (2004) for new approaches.

4 NEW HEURISTIC METHODS

This section describes two new heuristic methods, a greedy drop method (see Silver 2004) most common (MC) (I) and greedy spatial optimizer (GSO) (II, III) and illustrates how they work in reserve selection. First, greedy drop method is introduced. This method works opposite to common greedy methods. It starts with all selection units selected and removes units from a network until some restriction is violated.

4.1 Greedy drop method

Establishment of a reserve network often takes tens of years, for example plans for the Finnish national park network have been made in the 1920's, 1930's, 1950's, 1970's (anon 1976) and still some new national parks are being plannned. Even smaller scale reserve networks may take years to be completed. It is possible that during the establishment of reserve networks some areas may become unavailable or their quality as a reserve decreases (see Drecsler 2005). Thus we need to know which units outside the planned reserve network could compensate these unavailable units. The motivation to develop most common (MC) was to give an order to those selection units that are not in the reserve network selected by MSP (see Alidaee et al. 2001). MC gives an ordered list of areas, that can be used while seeking candidates to replace these unavailable areas (see Moilanen et al. 2005). MC can give different solutions to a reserve network selection problem from what commonly used greedy heuristics do (Tanskanen 1996a, 1996b) and also different types of selection rules can be applied.

Let us assume, that we have presence - absence data of features in a matrix A, $a_{ij}=1$ if feature j is present in unit i, otherwise $a_{ij}=0$. We have two objective functions, first to keep the rarest feature in each unit in the reserve network as widely distributed (common) as possible. Secondly, we maximize biodiversity score. We define biodiversity score as a sum of rarity scores of each selection unit. Rarity score for feature j is 1/ri, where $r_j = \sum_{i=1}^{I} a_{ij}$, $r_j>0$ and rarity score is 0 when $r_j=0$. Biodiversity score b_i is the sum of all rarity scores of features on it, $b_i = \sum_{j=1}^{J} (1/r_j)a_{ij}$. The number of occurrences of feature j in selected units is $z_j = \sum_{i=1}^{I} a_{ij} y_i$. Restrictions of the problem are $z_j \geq k_j$, j=1, ..., J, in other words feature j should be present in the reserve network at least k_j times, that is , feature j should be present in at least k_j units. For simplicity we suppose, that $k_1, ..., k_j$ have equal value k.

Operation

Drop methods start with all candidate units as selected and in each iteration remove the one having worst objective function value. MC uses a lexicographic order of objective functions and thus it uses one objective function at a time and in case of a tie it uses the next objective function to resolve a tie.

MC starts with all selection units marked as potentially selected, $y_i=1$, i=1, ..., I. These selection units are called candidate selection units until they are removed or MC has stopped .

Step 1: MC calculates $z_j = \sum_{i=1}^{I} a_{ij} y_i$ j=1, ..., J, that is, the number of occurrences of all features among the non removed selection units.

Step 2: MC calculates for each selection unit i for which is $y_i=1$ the number of occurrences of the rarest feature present ($a_{ij} > 0$) in the selection unit i: $s_i=\min(a_{i1}z_1, a_{i2}z_2, ..., a_{ij}z_j, ...a_{iJ}z_J)$, j=1, ..., J.

Step 3: Find the unit having highest value of s_i. If there are several units with same highest s_i value, then apply second objective function: select among these units the unit having highest biodiversity score b_i.

Step 4: If $\min(s_1, s_2, ..., s_I) \leq k$, MC terminates, because removing any selection unit would make the rarest feature of the reserve network represented less than k times and thus would violate the restrictions of the problem. If $\min(s_1, s_2, ..., s_I) > k$, MC removes the selection unit having the highest s_i value by setting y_i=0, where i is the index of the removed selection unit. Then MC starts a new removal cycle from step 1.

Speed

MC can be very slow compared to greedy heuristics in a case where the final solution contains very few selection units and is a small subset of the original selection unit set *I*. In those cases greedy heuristics outperform MC in speed (Tanskanen 1996a, 1996b), but with today's computing power this is not anymore so important and solutions times are for practical size problems rather minutes than hours. MC can remove all selection units having the same highest value $s_i > k$ in each cycle to improve the speed of optimization. Multiple deletions can lead to a solution out of the feasible region if the number of occurrences of the rarest feature falls under k, $\min(s_1, s_2, ..., s_I) \leq k$. In this case MC cancels the last multiple deletion and continues with single deletions. If the number of multiple deletions d is restricted by $d < \min(s_1, s_2, ..., s_I) - k$, the solution stays in the feasible region.

Uses of the method

Sometimes decision makers can more easily define rules to exclude selection units like MC does than to include them. Variants of MC can also be used to enhance the resulting set of greedy heuristics. In this case the result set of greedy heuristics is the starting set for MC and MC tries to remove selection units and thus improve objective function value, that is the number of selection units. MC serves as a basic method for MSP problems. In (I) a drop method was for the first time used in reserve selection.

4.2 Greedy spatial optimizer

Integrating spatial features into reserve selection optimization started in the literature with simple rules in ties like "select the site that is nearest in space to a site already selected" (Nicholls and Margules 1993). They used a greedy lexicographic heuristic optimization method and the spatial rule was the third rule in order to resolve ties. Thus, this spatial rule may not have been used in optimization if ties were solved with the second rule. This is the problem of greedy lexicographic heuristics, and the spatial targets may be totally ignored depending on non spatial data (see Lombard et al. 1995, 1997, Freitag et al. 1997).

Integrating spatial modelling and spatial optimization is challenging. While spatial calculations are done with geographical information system (GIS) software like Arcinfo (http://www.esri.com, 20.4.2005), optimization is done separately with optimization software. Spatial values can be calculated before optimization and then used in optimization. Possingham et al. (2000) minimized the length of the total boundary of the reserve network. Boundary lengths between selection units were calculated a priori with GIS. In Coda system (Bedward et al. 1992) the reserve network is adjusted after optimization, for example to follow roads or ownership boundaries. The reserve selection may need repeated optimization - spatial examination cycles. This separation of spatial targets from optimization affects the results and the decision maker's abilities to control the problem setting. There are two ways to avoid this, either to integrate optimization into GIS software (Hill et al. 2005) or to integrate spatial properties to optimization software. GSO uses the latter strategy by handling topologic structures during optimization.

Continuous areas or clusters of continuous areas in a reserve network are important to plants or animals dwelling in reserves, because these areas form reproduction or foraging ranges for them. Areas outside reserves may be hostile to animals and plants dwelling in reserves. This is especially true in human dominated fragmented landscapes (see Saunders et al. 1991). The importance of each continuous area or cluster has been ignored in reserve selection so far, because spatial objectives have been based on the features of a whole reserve network. This shortcoming led to a new modelling of spatial targets. In our new model each continuous area or cluster has its own spatial targets and thus objective functions. The number of continuous areas or clusters is not know a priori and, thus, the number of objective functions is unknown before optimization. GSO was developed to integrate optimization - spatial examination in reserve selection problems.

4.2.1 The spatial problem

We developed GSO to select a reserve network of old-growth forests in Northern Finland owned by Forest and Park Service (II). These reserves were selected from commercial and recreational forests. Results of reserve selection optimization were used in definition of the reserve network. The reserve selection problem was defined in conjunction with foresters and biologists from Forest and Park service. The problem definition was based on data available in the GIS of Forest and Park Service. Later, GSO was implemented to select a reserve network from forests owned by Stora-Enso (III) and UPM.

Forest GIS contains following data groups. Location data contains borders of selection units (stands). The information of wood production contains timber volumes (diameter, height) by age and tree species, the amount of dead wood, operation history and plans for timber production. Other features of stands stored in GIS are soil properties, vegetation types, names and amounts of endangered species and real estate properties. We define the reserve selection problem according to the data available and the knowledge of the environmental needs of old forest dwelling species.

The reserve selection problem is formulated as a mixture of generalized goal programming problem and multiobjective optimization problem. The term goal is used here in the sense of generalized goal programming, where constraints are part of the goals (Ignizio 1983, Miettinen 1999). We call hard (rigid) goals those that are also constraints and others (object functions) we call soft (flexible) goals. Goals are divided into two groups, spatial goals and non spatial goals. All spatial goals are defined as soft goals. Non spatial goals consists of hard goals, that are constraints of the problem and possible soft goals that reflect the preferences of decision makers but need not to be reached. Spatial goals are hidden in spatial function definitions and thus they resemble normal objective functions of minimizing problem. Non spatial objectives are part of a minimizing problem.

4.2.2 Problem definition

The problem definition consists of non spatial and spatial parts. First we define non spatial objectives and constraints. The non spatial objective is to minimize the cost of a reserve network,

$$\text{Minimize} \sum_{i=1}^{I} c_i y_i$$

as in MSP. Unlike in MSP, constraints of features J are divided into two separate groups, soft and hard. We denote these sets by S and H, respectively. Constraints are amounts of features $h \in H$ in the reserve network

$$\sum_{i=1}^{I} a_{ih} y_i \geq r_h, \quad \text{for each } h \in H, \quad \text{where } y_i = 0 \text{ or } 1 .$$

Soft constraints are like soft goals in generalized goal programming and we call them soft goals. Goals $s \in S$ form a set of objectives, where goals should be reached and no penalty is paid for exceeding goals, we have

$$\text{Minimize} \quad \max(r_s - \sum_{i=1}^{I} a_{is} y_i, 0), \text{ for } s \in S, \text{ where } y_i = 0 \text{ or } 1 .$$

The set S can be empty and then the problem definition is like the one in MSP. Further spatial goals are sizes of continuous areas, sizes of clusters and evenness of spatial distribution of continuous areas. Here we have only one spatial function of each type, but there could be separate functions for example for different forest types, swamps or meadows.

Decision makers define preferred sizes of continuous areas with the function f_a: $\mathbb{R} \to \mathbb{R}$. It is a function of the size of continuous area k in the reserve network, $A(Ca_k)$. In (II), we set the goal for the size of continuous areas to be between 100 and 200 ha as mentioned before, further details and biological justification can be found in (II). Function f_a was increasing from 0 to100 ha, constant between 100 and 200 ha and decreased with areas over 200 ha. We maximize f_a with each candidate continuous area by defining a set of objectives: $\text{Maximize } f_a(A(Ca_k)), \ k \in NA$, where NA is the set of continuous areas in the reserve. The number of continuous areas Na is not known a priori. The number of objectives is Na.

Function $f_g: \mathbb{R} \to \mathbb{R}$ describes decision makers' preference of the size of clusters. On biological grounds we can assume, that this function is a non-decreasing function of the size of a cluster. The larger cluster and connectivity, the better reserve network is for many plants and animals. For all cluster we have objectives

$$\text{Maximize } f_g(A(Cl_l)),\ l \in NL\,.$$

The number of objectives Nl is not known a priori. The preferred size of a cluster is larger than that of a continuous area, hence, clusters should consist of several continuous areas.

We define evenness of reserve network by d_{i^*}, the minimum distance from one continuous area to its closest neighbour. Smaller sum of d_{i^*} indicates more clustered distribution of continuous area and the sum will be 0 with only one continuous area. Decision makers define function f_d: $\mathbb{R} \to \mathbb{R}$, as a function of d_{k^*} to describe their preferences to this distance. The goal can be to distribute selected areas over all parts of the planning area. Then f_d is an increasing function of d_{i^*}. The objectives are to maximize f_d with each continuous area,

$$\text{Maximize } f_d(d_{k^*}),\ k \in NA\,,$$

the number of objectives Na is not know a priori.

The problem is as converted to a minimizing problem

$$\text{Minimize} \sum_{i=1}^{I} c_i y_i, \tag{10}$$

$$\text{Minimize} \quad \max(r_s - \sum_{i=1}^{I} a_{is} y_i, 0),\ \text{ for each } s \in S\,, \tag{11}$$

$$\text{Minimize} - f_{ak}(A(Ca_k)),\ \text{ for each } k \in NA, \tag{12}$$

$$\text{Minimize} - f_{gl}(A(Cl_l)),\ \text{ for each } l \in NL, \tag{13}$$

$$\text{Minimize} - f_{dk}(d_{k^*}), \quad \text{for each } k \in NA, \tag{14}$$

$$\text{subject to} \sum_{i=1}^{I} a_{ih} y_i \geq r_h, \quad \text{for each } h \in H \text{, where } y_i = 0 \text{ or } 1. \tag{15}$$

4.2.3 An overview

GSO is a greedy iterative heuristic optimizer which adds selection units to the reserve network according to their value for the reserve network that has been so far created during the selection process. The value of a candidate selection unit is calculated as a weighted sum of spatial and non spatial objective function values of each candidate selection unit that is divided by the cost of the selection unit. In this way we can compare values per cost and handle on equal terms units of different sizes or prices. GSO uses three types of spatial objective functions in reserve selection. The first spatial objective function is continuous area function based on the size of a continuous area. The second is connectivity function measuring the increase of a cluster and third is isolation function measuring the increase of evenness of distribution locations of continuous areas. Spatial objective functions are calculated for each candidate selection unit using the continuous area and the cluster, that it would belong to. In the selection process typically hundreds or thousands of spatial objective functions are calculated and results are compared in each iteration. The selection unit that has greatest value in each iteration is added to the reserve network and thus GSO makes locally best selection during selection process.

4.2.4 Operation

GSO operates by adding one candidate selection unit to the reserve network in each iteration.

Decision makers give a priori the non spatial goals $r_1, \ldots, r_J$ of features $1, \ldots, J$. These goals are assumed to be minimum levels of features in the reserve network and, thus, there is no penalty of exceeding goals. After n iterations n selection units have been selected: $\sum_{i=1}^{I} y_i = n$, and the present achievement of goal j is $p_j = \sum_{i=1}^{I} a_{ij} y_i$. If feature j has $p_j < r_j$, we define the gap of feature j to be r_j-p_j. To make gaps of different features comparable to each other we normalize them by dividing with r_j and we get a normalized gap $(r_j - p_j) / r_j$. Each candidate selection unit i has the amount a_{ij} of the feature j. In the selection of a candidate unit GSO considers only the part of a_{ij}, that would not exceed r_j, that is $\min(a_{ij}, r_j - p_j) / r_j$. Then we consider only those features that are not yet fulfilled ($p_j < r_j$) with already selected selection units by taking only positive normalized gaps $\max\left[(\min(a_{ij},\ r_j - p_j) / r_j),0\right]$.

Some features may be reached faster than others. Features may be correlated in candidate selection units. This correlation means that features k, l $\in J$ exist in same selection units more often than would be assumed by random distribution of features among selection units 1, ..., I. We assume a situation where the normalized gap of feature k $(r_k$-$p_k)/r_k$ is small and positive. The normalized gap of feature l is relatively large compared to the normalized gap of k. The correlation of features l and k may lead to large excess of feature k. Selection units containing feature l are selected after the goal of feature k is reached, and selection units having feature l have often also feature k. To avoid this we introduce a dynamic weight $(1$-$p_j/r_j)$ for each feature j, that goes from one to zero while the amount of feature j in the reserve network p_j reaches its goal r_j. This dynamic weight balances the speed by which different goals are reached during iterative adding process.

Decision makers have to define non-negative weights w_1, ..., w_J a priori for all goals 1, ..., J, zero weight omits the goal from optimization, positive values support goals. Zero values can be used for evaluation purposes, and to test changes in decision maker's preferences without changing goals (Miettinen 1994, Romero 2001). Weights may reflect importance of objective to decision makers but also marginal rates of substitution between objective functions as in many optimization methods (Miettinen 1999). In the latter case a low weight may reflect decision makers willingness to exchange a larger amount of decrease in this objective to smaller amount of increase in a higher weighted objective.

The weighted amount of non spatial features of a candidate selection unit i is

$$q_i = \sum_{j=1}^{J} w_j(1 - p_j / r_j)\max((\min(a_{ij}, r_j - p_j) / r_j),0) \qquad (16).$$

We call q_i the non spatial value of selection unit i.

There are three spatial objective functions: Continuous area function f_a, connectivity function f_c and isolation function f_d. Decision makers define these objective functions a priori.

Continuous areas

Function $f_a: \mathbb{R} \rightarrow \mathbb{R}$ is the objective function measuring the intended size of continuous area Ca. Decision makers define their preferences of sizes of any continuos area in the reserve network with function f_a. Let us assume, that the candidate selection unit i is selected. The candidate selection unit i belongs to certain continuous area Ca of already selected areas. If no neighbours of i are already selected, the continuous area Ca contains only selection unit i. The value of f_a for selection unit i is calculated with this area A(Ca). The area A(Ca) where i belongs can change while new candidate areas are selected in the iterative process. A candidate selection unit i would belong to the continuous area Ca_k, if it where added. After adding unit i we denote this new larger continuous area by Ca_{k+i}. We calculate the size of the continuous area it would belong before $A(Ca_k)$ and after adding this particular selection unit i, $A(Ca_{k+i})$. The continuous area objective function is for each candidate selection unit $f_{ai}(A(Ca_{k+i})) - f_{ai}(A(Ca_k)),\ i \in I, k \in NA$. Na often changes when new selection units are added to the reserve network. Na decreases when the selection unit i joins two or more continuous areas together. Na increases when the selection unit i creates a new continuous area.

We use the difference of f_a values before and after possible selection of candidate selection unit to guide the selection to produce continuous areas of preferred size.

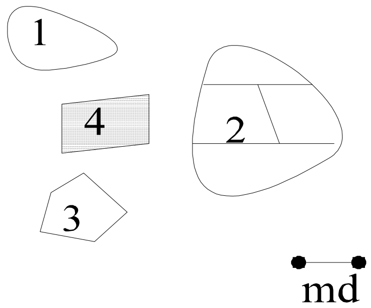

FIGURE 2 The selection unit 4 creates a cluster containing continuous areas1-4 with inter area distance md

Connectivity

Let us assume that a candidate selection unit i is selected and the cluster it belongs is Cl_k. We denote the area difference of cluster Cl_k the selection unit i belongs to and largest cluster that originate from Cl if unit i is removed from the reserve network by $\Delta A(Cl_{k+i})$.

Connectivity of selection unit i is measured as absolute value of area difference $\Delta A(Cl_{k+i})$. The connectivity depends on which candidate units are selected to the reserve network and may change during iterative adding of candidate units. The smallest change is A(i), the area of a candidate unit i.

In Figure 2 candidate selection unit 4 would make one large cluster containing continuous areas 1-4. Before adding selection unit 4 the largest cluster were continuous area 2, because all distances between continuous areas 1-3 were longer than md. Thus the area difference of cluster 2 to which 4 would belong is $\Delta A(Cl_{2+4})=\{A(1)+A(2)+ A(3)+A(4)-A(2)\}=A(1)+A(3)+A(4)$. Decision makers define their preferences for this connectivity potential with object function $f_c : \mathbb{R}\to\mathbb{R}$. Increasing function f_c of $\Delta A(Cl)$ supports large clusters. This is some different from objective function f_g, that describes the preferred sizes of clusters. We assume that decision makers prefer forming large clusters. Thus we optimize the increase of the cluster size instead of the size of a cluster. In every iteration we calculate for each candidate selection unit the connectivity value $f_{ci}(\Delta A(Cl_{k+i})),\ i \in I, k \in NL$.

Isolation

Isolation of a candidate selection unit i is defined as the distance to closest already selected selection unit d_{i*}. Isolation objective function $f_d : \mathbb{R} \rightarrow \mathbb{R}$, a function of d_{i*}, increases evenness of spatial distribution of continuous areas when f_d is an increasing function of d_{i*}. Then, f_d gives higher objective function values to those selection units that are far away from any already selected selection unit. This also serves as a generator for new continuous areas and favours stepping stone creation in the middle of two continuous areas. This is especially important in creating stepping stones when distances between continuous areas are over two times md, the maximum inter cluster distance. The isolation objective function value is $f_{di}(d_{*i}),\ i \in I$ and it is calculated for each i in each iteration.

Spatial weights

Decision makers give also a weight for each spatial objective function. These weights reflect the importance of each spatial goal. These weights are called wa for continuous area function f_a, wc for connectivity function f_c and wd for isolation function f_d. Decision makers define the relative importance of different spatial goals with wa, wc, wd. Changes of spatial weights can have a remarkable effect on results, see Siitonen et al. (2003). The spatial value of candidate selection unit i is

$$s_i = wa f_a(A(Ca_i)) + wc f_c(\Delta A(Cl_i)) + wd f_d(d_{i*}) \quad (17).$$

GSO calculates s_i for each candidate selection unit. Functions f_a, f_c and f_d need to be defined for all parameter values of A(Ca), Δ A(Cl) and d_{i*}, respectively, but no assumptions of continuity of functions f_a, f_c and f_d is needed. Examples of function definitions are given in II and III.

Decision makers define how spatial objectives are compared with non spatial objectives a priori with a total spatial weight ws. It is the weight of spatial goals relative to one, the weight of non spatial objectives. Unlike other spatial weights, ws is recalculated after each iteration. The actual value of ws after n iterations is, for all candidate selection units

$$ws_n = ws(\max_{k \in I}(q_k) / \max_{m \in I}(s_m)).$$

Maximum is used here, because greedy methods select the area having the best objective function value. This dynamic scaling is done because on the average the non spatial objective function values $q_1, ..., q_I$ decrease during selection process and spatial objective values $s_1, ..., s_I$ usually increase at the beginning of optimization. The decrease of q_i comes from the dynamic weighting of non spatial objectives and decreasing gain ratios of GSO. GSO chooses always the selection unit having best objective function value. Increase of $s_1, ..., s_I$ comes from spatial functions. First units selected cannot have high connectivity or continuous area values because almost no selection units are selected. If spatial goals are almost reached, on the average $s_1, ..., s_I$ starts to decrease depending on definitions of f_a, f_c and f_d. Thus, fixed ws would not reflect the decision maker's opinion, but merely a stronger spatial weighting iteration after iteration. With dynamic ws_n decision makers can decide spatial and non spatial weights separately.

The costs of selection units $c_1, ..., c_I$ are given a priori. GSO selects in each iteration the candidate selection unit having larges value of weighted sum where spatial (17) and nonspatial (16) objective functions are divided by cost, in other words $o_i = \dfrac{ws_n s_i + q_i}{c_i}$. The value o_i changes in each iteration for a candidate selection unit i, because the achievement of goals changes and spatial arrangement of already selected selection units changes.

The iterative adding of candidate selection units stops, when the reserve network fulfills restrictions: $\sum_{h=1}^{H} \max((r_h - p_h),0) = 0$ or no candidate unit supports hard goals $\sum_{i=1}^{I} ((1 - y_i)\sum_{h=1}^{H} a_{ih}) = 0$. The drawback of greedy heuristics is that they may continue to iterate with only one or few restrictions violated and include new selection units. This may lead to a situation where the amount of many features h in the reserve network are larger than r_h. It is possible, that some selection units could be removed from the reserve network without violating restrictions and resulting with an improved objective function value. This was shown with a bidirectional variant of GSO (Tanskanen 2000).

In practice one or more meetings have been arranged before applying optimization methods to the reserve selection problem. In these meetings foresters and biologists have described their targets and restrictions for the problem. These partly verbal descriptions of the problem have been translated to a numerical form in cooperation with them. We have used the data available in forestry GIS and specified the optimization problem based on that data. The forestry GIS data was collected for other purposes such as wood production and forest planning. Certain data, including distribution of endangered species was not systematically collected over planning area. Therefore, false negatives must be considered while applying optimization and when interpreting results of optimization. No data collection or field surveys were done specially for these optimization exercises.

GSO was used in real life planning situations and we did produce several scenarios for decision makers. These scenarios differed in constraints and weights, and they were named as 'ecological' with aims to get more reserves, or 'commercial' preferring more wood production. Spatial preference varied from some large continuous areas to several small (see SLOSS debate in Haila and Kouki 1994, Berglund and Jonsson 2003) . Examples of applying GSO are found in II and III.

5 CONCLUSIONS

Optimization in reserve selection has evolved during last twenty years. The first ten years were mainly testing of greedy heuristic methods in new situations. During the last ten years, the complexity of reserve selection problems has increased and new optimization methods have been employed. There are currently two major ways to optimize reserve selection, LP/MIP and greedy heuristics. The development of LP/MIP methods is carried out outside the conservation community for all purpose use, but new variants of heuristics have been developed in connection with reserve selection problems. Thus, conservationists are more familiar with heuristics which affects the selection of optimization methods in reserve selection.

The problem of reserve selection varies with biological targets, location and size of the area concerned, data available, land-use conflicts and other factors. The diversity of cases supports several different methods for reserve selection optimization. LP/MIP is preferred when problems are easily solvable, but there is still use for heuristics and other methods especially with spatial goals. In forestry, heuristics have partly replaced LP/MIP since 1990's due to new spatial and environmental constraints and objectives (Bettinger and Chung 2004), an example of spatial heuristics is in Kangas et al. (2000). For example, the drop method, a variation of greedy heuristics, was further developed to a spatial optimizer (Cabeza et al. 2003).

When we developed a new heuristic method for the spatial reserve selection the following arguments were expressed by the research team. First, it should consider different spatial aspects simultaneously. Second, it should be able to solve the real size problems with modest PC computer in a reasonable time. Third, it should be able to produce different scenarios depending on decision makers needs fairly easily. Fourth, it should be able to use GIS data of features and location information as easily as possible. Location information was too large to be used directly during optimization and distance calculation was found to be too slow. Thus our solution was to calculate distance and size matrixes a priori and use these matrixes in optimization. Other above listed arguments were fulfilled, although no user interface for GSO was implemented.

Especially novel idea of GSO is the implementation of spatial objectives. The continuous area function f_a controls the size of selected areas and has an effect on the proportional amount of the core. The connectivity function f_c creates corridors and stepping stones to increase colonization and movement between reserves (MacArthur and Wilson 1963, Diamond 1975, Helliwell 1976, Cook 1995, Hanski 1999, Briers 2002). The isolation function f_d constrains the reserve network to a more even distribution of reserves. These spatial goals are favoured with functions defined in II and III, but changing the function definitions alters spatial objectives. The ecological background of the chosen spatial functions is presented in detail in II and III.

Future challenges include deeper integration of spatial properties to GSO to handle more complex spatial goals. The development of dynamic weights (Tanskanen 2000) and stochastic selection as in simulated annealing would improve the performance of GSO. The method's sensitivities to different weight settings need more detailed research. The results of (III) show clearly that altering weights produces remarkably different solutions and also reflects the preferences of decision makers. Furthermore, method's capability of finding different good solutions by adjusting weights must be considered.

The gap between theory and practice is noticeable even after all the development in reserve selection optimization. New methods have not been used enough in practice and more cooperation between scientists and conservation practitioners is needed (Prendergast et al. 1999). This is the major challenge in the nearest future, because the speed of nature destruction is so high and we do not have much time left. In future climate change may change optimal location of reserves in a way we can not precise estimate(Pyke et al. 2006). This is due rising temperatures, changing precipitation and rising sea-level that affect biotas. An example of this is a seal reserve, that in future lies under sea-level.

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YHTEENVETO (FINNISH SUMMARY)

Suojelualueita tarvitaan luonnon monimuotoisuuden turvaamiseksi ihmistoiminnan levittäytyessä yhä laajemmalle. Lajeja ja elinympäristöjä katoaa jatkuvasti ja yhä useampi laji on sukupuuton partaalla.

Suojelualueita valittiin pitkään niiden kauneuden, maan edullisuuden tai omistusolojen perusteella. Näin suojelualueverkosto Suomessakin painottui etäisiin, tuottamattomiin ja valtion omistamiin Lapin erämaihin.

Järjestelmällinen suojelualueiden valinta alkoi luokittelemalla ja järjestämällä potentiaalisia suojelukohteita niiden lajiston runsauden tai uhanalaisuusluokitusten perusteella. Tämä johti useasti samojen lajien tai elinympäristöjen suojeluun, usenmiten runsaslajisten alueiden suosimiseen. Luokittelumenetelmät eivät huomioineet syntyvää suojelualueverkkoa vaan tarkastelivat kutakin potentiaalista aluetta omana yksikkönä ilman laadullista tai sijainnillista suhdetta muodostettavaan suojelukokonaisuuteen .

1980-luvulla herättiin tähän ongelmaan ja ensi kerran käytettiin optimointia kokonaisten suojelualueverkkojen suunnittelussa. Tämä johti täydentävyyden käsitteen käyttöön, kuinka suojelualueverkoston osat täydentävät toisiaan lajistollisesti, elinympäristöittäin ja luomalla ekologisia yhteyksiä eri suojelualueiden välille.

Aluksi optimoinnissa käytettiin tarkoitukseen kehitettyjä heuristisia ahneita menetelmiä, mutta 1990 luvulla myös sekalukuoptimointia. Heuristiset menetelmät ovat edelleen käytössä erityisesti sijaintioptimointia sisältävissä tehtävissä.

Tässä työssä esitetään kaksi heuristista menetelmää, poistava heuristinen optimointi (I) ja ahne heuristinen sijaintioptimointi (II ja III). Menetelmät on kehitetty erityisesti näitä sovellutuksia varten, mutta ovat helposti muokattavissa moniin eri suojeluvalinnan tilanteisiin. Poistavan menetelmän etuna on sen tuoma järjestys menetelmän poistamille alueille. Tätä järjestystä voidaan käyttää eri suunnitteluvaihtoehtojen evaluointiin. Sijaintioptimoinnissa lähtökohtana olivat suomalaiset metsätietokannat ja niiden tietosisältö. Menetelmän tavoitteena on valita kustannustehokkaasti sijainniltaan ja laadultaan hyvä metsäkuvioiden joukko talouskäytön ulkopuolelle.

Molemmissa menetelmissä minimoidaan kustannuksia, joten rajoitteet tulee valita siten, että ekologiset ym. tavoitteet saavutetaan. Menetelmiä on kehitetty yhdessä suojelupäätöksistä vastaavien tahojen kanssa.