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Conservation planning of threatened flora in northwest Iberian Peninsula: a comparison of two reserve selection tools

Ricardo Reis Alves Soares Cardoso

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2013

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Todas as correções determinadas pelo júri, e só essas, foram efetuadas.

O Presidente do Júri,

Porto, ______/______/_________

Resumo

O planeamento sistemático da conservação é um conjunto de etapas utilizadas para a identificação eficiente de áreas e implementação de ações de conservação que garantam a representação e a persistência das espécies. Uma importante etapa do planeamento sistemático para a conservação consiste na seleção de novas áreas de conservação, quer como novas redes de reservas, quer para complementar redes de áreas de conservação já existentes. A seleção de reservas é geralmente feita com recurso algoritmos de seleção de reservas. Nesta dissertação, apresentam-se os dois principais tipos de problemas de seleção de reservas e faz-se uma revisão dos vários tipos de algoritmos existentes para os resolver, nomeadamente algoritmos heurísticos, metaheurísticos e exatos. Em seguida, são descritos em detalhes dois programas de planeamento de conservação – Marxan e ConsNet. Ambas as ferramentas implementam algoritmos metaheurísticos: *simulated annealing* no caso do Marxan, e *tabu search* no ConsNet. Investigou-se a performance relativa destes programas no problema de encontrar o menor conjunto de locais garantindo que os elementos de conservação atinjam metas de representação predefinidas. Para tal, usaram-se as distribuições observadas e as previstas de 11 espécies de plantas raras ou ameaçadas na Galiza e Norte de Portugal. Compararam-se os atributos espaciais e a sobreposição das soluções. Os resultados mostram que o ConsNet produziu redes de conservação com menor área, enquanto o Marxan produziu soluções mais compactas. Ambos os programas selecionaram locais nas mesmas áreas geográficas, embora as células selecionadas não tenham tido uma elevada sobreposição. Com base nestes resultados, sugere-se o uso do ConsNet quando o objetivo é encontrar a menor área, e o Marxan quando uma solução mais compacta é mais importante que uma de menor custo.

Palavras-chave: Algoritmos de seleção de reservas; ConsNet; Galiza; Marxan; Norte de Portugal; Planeamento sistemático da conservação; Simulated annealing; Tabu search

Abstract

Systematic conservation planning is a framework developed to efficiently identify conservation areas and implement conservation actions that guarantee species representation and persistence. An important stage of systematic conservation planning is the selection of new conservation areas, either as a new reserve network or to complement existing conservation area networks. Reserve selection is often done with the support of computer algorithms. In this dissertation, the two main types of reserve selection problems are presented and various types of reserve selection algorithms are reviewed, specifically heuristics, metaheuristics and optimal algorithms. Then, Marxan and ConsNet, two conservation planning software packages are described in detail. Both tools implement metaheuristic algorithms: simulated annealing in the case of Marxan, and tabu search in ConsNet. We investigated the relative performance of these programmes in finding the smallest set of sites such that conservation features meet predefined targets. To do this, we used data on the observed and predicted distributions of 11 rare or threatened plant species in Galicia and Northern Portugal. We compared the spatial attributes of the solutions and their overlap. Results show ConsNet produced smaller reserve networks, while Marxan generated more compact solutions. The same broad geographic regions were selected by both packages for expansion of the existing protected areas, although the specific cells selected did not show a high overlap. Based on these results, we suggest using ConsNet when attempting to find the smallest area, and Marxan when compactness is more important than minimizing the cost.

Keywords: ConsNet; Galicia; Marxan; Northern Portugal; Reserve selection algorithms; Simulated annealing; Systematic conservation planning; Tabu search

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List of Abbreviations

BLM – Boundary Length Modifier

CLUZ – Conservation Land-Use Zoning software

CR – Critically Endangered

DNS – Dynamic Neighbourhood Selection

EN – Endangered

GIS – Geographic Information System

GUI – Graphical User Interface

ID – Identification

IUCN – International Union for Conservation of Nature

MASTS – Modular Adaptive Tabu Search

NP – Non-Deterministic Polynomial Time

PA – Protected Areas

PANDA – Protected Areas Network Design Application

RBO – Rule-Based Objective

SDM – Species Distribution Models

SLOSS – Single Large or Several Small

SPF – Species Penalty Factor

UTM – Universal Transverse Mercator

US – United States of America

ZC – Zonae Cogito

Chapter 1. Introduction and objectives

1.1. The decline of biodiversity and the role of protected areas

Biodiversity can be defined as the variation among living organisms, including diversity and interaction within species, between species and of ecosystems (Carvalho, 2010; United Nations Environment Programme, 1992). Biodiversity plays a key role in ecosystem functioning and the provision of ecosystem services (Millennium Ecosystem Assessment, 2005). A recent review found a large number of ecosystem services benefit from an increase in biodiversity, some suffer mixed effects and a small number are hindered by higher biodiversity (Cardinale et al., 2012).

In spite of its significance, biodiversity is declining at an alarming rate, only comparable to the last mass extinction (Koh et al., 2004; Pimm et al., 1995; Wake and Vredenburg, 2008). This loss of biodiversity has led to the degradation of an estimated 60% of Earth's ecosystem services over the last 50 years(Millennium Ecosystem Assessment, 2005). The major drivers of this decline include overexploitation of biological resources, habitat conversion and fragmentation, climate change, proliferation of invasive species, pollution and genetic depletion (Davies et al., 2006; Ehrlich and Pringle, 2008; Parmesan, 2006; Thomas et al., 2004).

One of the approaches to address this biodiversity decline is through in situ protection, namely with the designation of protected areas (Margules and Pressey, 2000; Primack, 2006). Protected areas are one of the most effective methods for the protection and conservation of biodiversity (Rodrigues et al., 2004), and the global coverage of protected areas has steadily increased in the last decades (Mulongoy and Chape, 2004). In 2004, Rodrigues et al. assessed the global protected areas network for its coverage of the distribution of 11,633 terrestrial vertebrates, and observed that 1,424 (12%) species were not represented in any of the protected areas. Moreover, outcomes for Rodrigues et al. assessment highlighted an underrepresentation of threatened species, and from such species, 20% were identified as gap species.

1.2. Systematic Conservation Planning

Conservation planning is the process of locating, configuring, implementing and maintaining areas that are managed to promote the persistence of biodiversity and other natural values (Pressey et al., 2007). In conservation planning, species richness, rarity, level of endemism or threat or other geographic, social or economic indices are used to prioritize areas to conserve (Carvalho, 2010). Global key areas for conservation have been identified by several biodiversity conservation organizations using these strategies (Brooks et al., 2006). In order to establish explicit conservation goals that can be translated into quantitative targets towards which progress can be measured, a new framework has been developed called systematic conservation planning (Margules and Pressey, 2000; Pressey and Bottrill, 2008; Sarkar and Illoldi-Rangel, 2010).

Systematic conservation planning is a framework developed to efficiently identify conservation areas that guarantee species representation and persistence (Margules and Pressey, 2000; Moilanen et al., 2009) Representation refers to the need to represent all features of biodiversity, preferably at all levels of organization. Persistence refers to long-term survival of the species and other features of biodiversity, achieved by maintaining the ecological and evolutionary processes that sustain them (Carvalho, 2010; Margules and Pressey, 2000). Both of these goals should be achieved with as much economy of resources as possible, because resources for biodiversity conservation are limited and their allocation should be optimized. Additionally, considering such resources could potentially be used to promote human well-being, their efficient allocation is an ethical imperative (Sarkar and Illoldi-Rangel, 2010).

Systematic conservation planning has a number of distinctive features, such as assessing the achievement of conservation goals in existing reserves prior to the planning process and the use of explicit methods to locate and design new reserves (Margules and Pressey, 2000). Additionally, it is guided by the following set of key principles (Carvalho, 2010; Wilson et al., 2009a):

- **Comprehensiveness and representativeness:** a comprehensive conservation network includes a fraction of each element of biodiversity; while a representative conservation network assures that each biodiversity element is sufficiently represented, for example by including viable populations.
- **Complementarity and efficiency:** efficiency refers to the need to achieve conservation goals at the lowest possible cost. Complementarity ensures that the different areas of a conservation network complement each other in terms of the type and amount of biodiversity elements they contain. It is a measure of the extent to which an area contributes unrepresented features to an existing area or set of areas (Margules and Pressey, 2000).

- **Flexibility and irreplaceability:** flexibility can be defined as the number of possible combinations of sites that can be selected to attain the representation targets efficiently. Irreplaceability, on the other hand, is a measure of how indispensable a site is for meeting the representation targets. An irreplaceable site is one without which one or more targets will not be met (Carwardine et al., 2006).
- **Adequacy:** this principle ensures a conservation network promotes the persistence and evolution of the biodiversity elements represented. The lack of data or limited understanding of the ecological and evolutionary processes that sustain species persistence mean this principle is commonly neglected. It has been addressed by setting targets based on population viability analyses or probabilities of persistence, including spatial configuration criteria such as reserve size, connectivity and shape and identifying surrogates for ecological and evolutionary processes (Carvalho, 2010).

Margules and Pressey (2000) originally described six stages in the process of systematic conservation planning. Pressey and Bottrill (2008) describe 5 additional stages. Their proposed framework is depicted in **Erro! Auto-referência de marcador inválida.**. Sarkar and Illoldi-Rangel (2010) offer another protocol for systematic conservation planning, which is not as detailed in the early stages but has additional steps at the final stages (Figure 2) This protocol also makes explicit the main interactions between the stages and the degree to which they are well understood.

It is important to note that, more than being a theoretical framework, systematic conservation planning is already being considered in the decisions of organizations, influencing legislation and policy and accomplishing results on the ground and in the water (Pressey and Bottrill, 2008).

1.3. Objectives

This dissertation has three main objectives:

1. To review the concepts and technical choices that underlie the development of conservation planning software tools.
2. To describe two spatial conservation prioritization software tools: ConsNet (Ciarleglio et al., 2009) and Marxan (Ball et al., 2009).
3. To compare the performance of ConsNet and Marxan, using a subset of the dataset from BIODIV_GNP "Threatened Biodiversity – Galicia and Northern Portugal" project, in order to test distinct tools for their adequacy in the establishment of complementary areas of protection for threatened plant species.

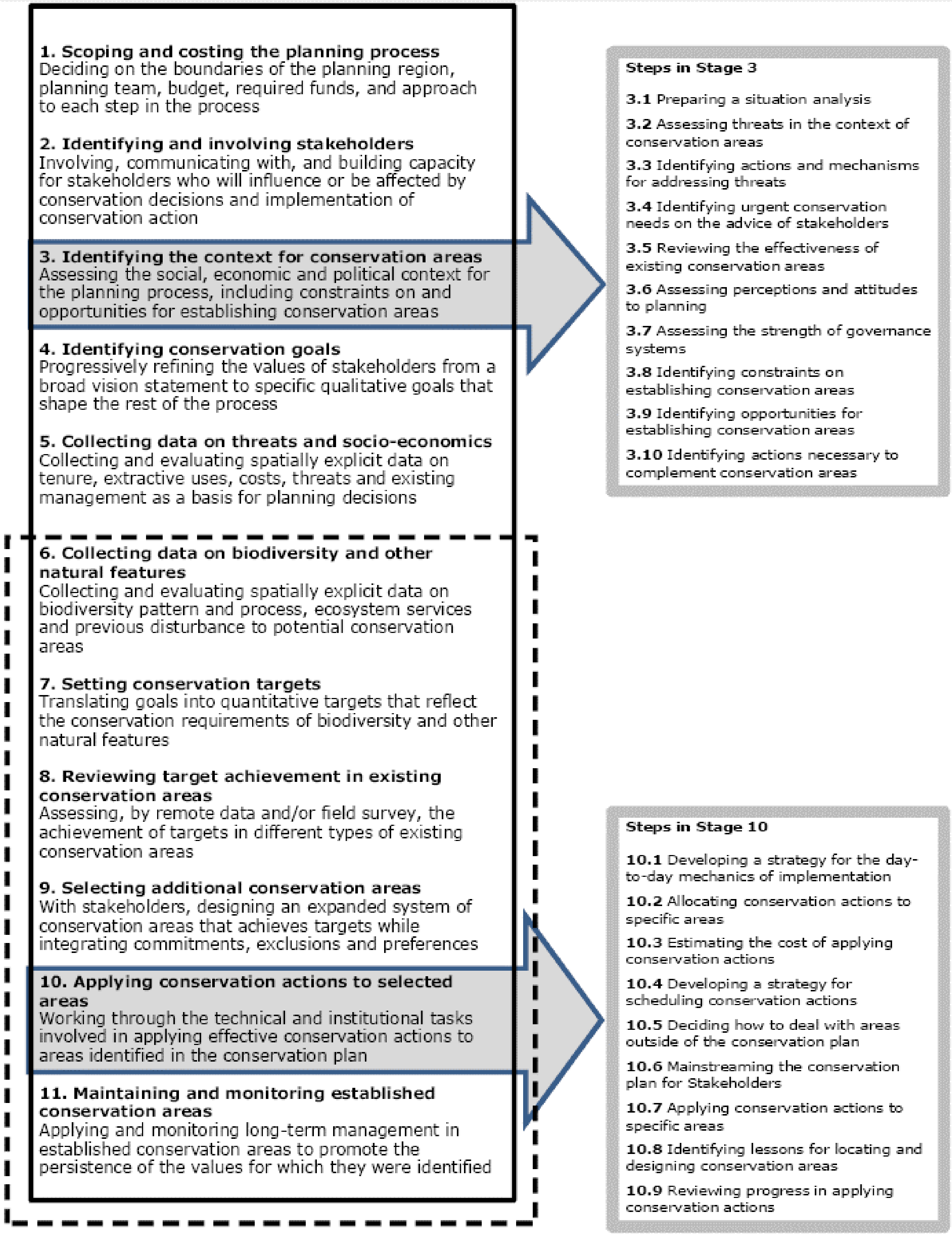

Figure 1. An evolving framework for conservation planning with 11 main stages. Text under the heading for each stage summarizes the main issues to be addressed (see Margules & Pressey 2000; Cowling & Pressey 2003 for more detail on most stages). For convenience, the process is depicted as a linear sequence, but in reality some stages will be undertaken simultaneously and there are many feedbacks from later to earlier stages. Among the reasons for feedbacks are revisions of earlier steps to deal with surprises, including unexpected opportunities. The dashed rectangle contains the stages described by Margules and Pressey (2000). The steps involved in stages 3 and 10 are included to emphasize the diversity of tasks and decisions involved. Source: Pressey and Bottrill (2008).

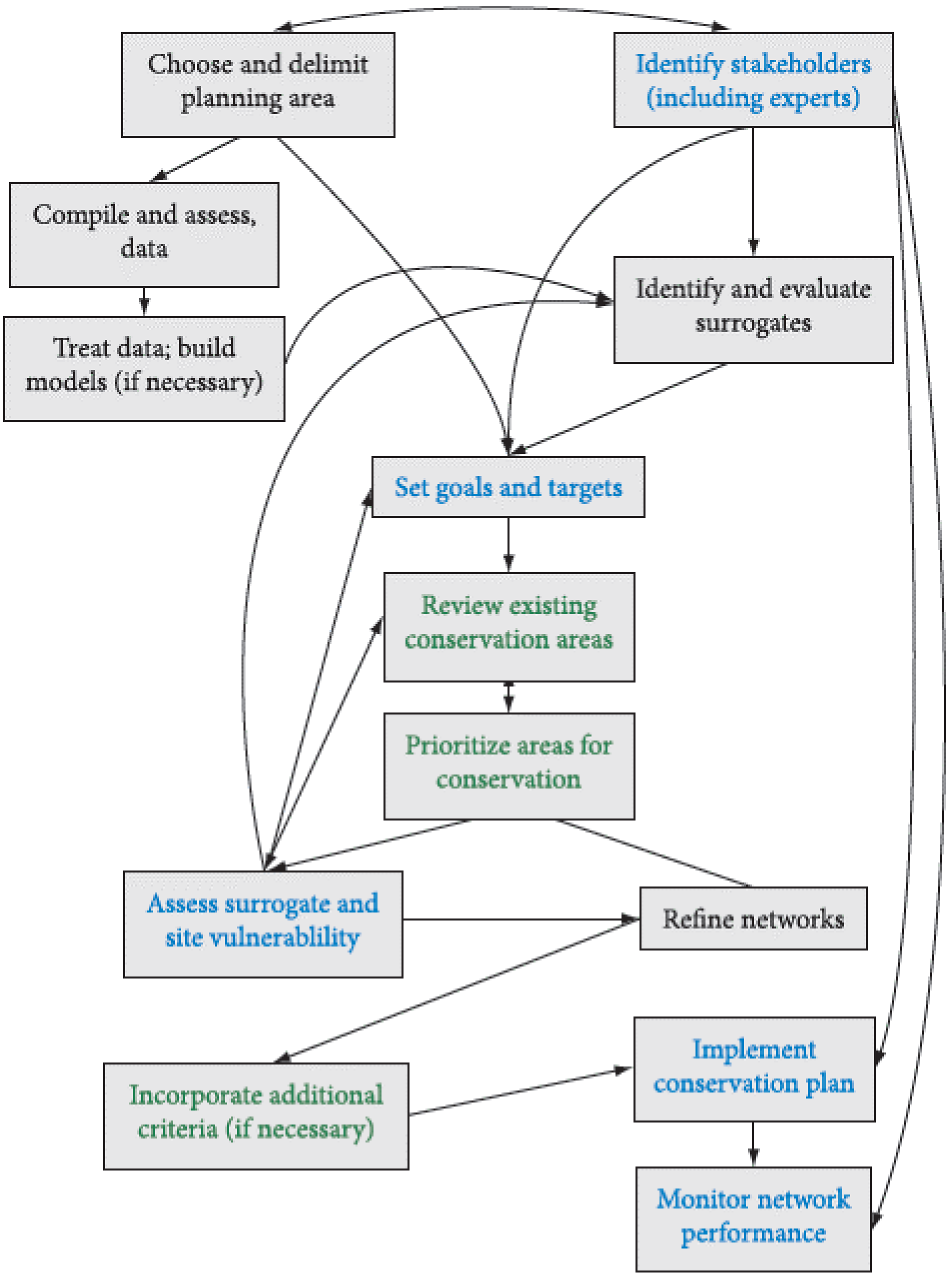

Figure 2. Stages of Systematic Conservation Planning. Arrows indicate which components directly influence which others. A bidirectional arrow indicates feedback. Only the major interactions between the components are shown. There is potential for feedback between almost any two components of this framework. Boxes with text in green indicate aspects that are well-understood, those with text in black are aspects which are fairly well-understood, and those with blue text are areas that remain poorly understood and subject to much ongoing research. Source: Sarkar and Illoldi-Rangel (2010).

Chapter 2. Reserve selection tools

2.1. Introduction

Early efforts at reserve design were guided by the equilibrium theory of island biogeography and related biogeographical theory (Margules and Pressey, 2000; Possingham et al., 2000; Sarkar et al., 2006). Emphasis was on the size, shape and number of reserves. This body of theory prescribes general guidelines about the preferable way to design a reserve network. For instance: bigger reserves are better than small reserves; long and thin reserves with a high edge-to-area ratio are worse than compact, circular ones; reserves should be connected by habitat corridors instead of isolated from each other, and so on (Margules and Pressey, 2000; Possingham et al., 2000). An early debate, known in the scientific literature as the SLOSS debate (single large or several small), occurred over whether species richness is maximized in one large reserve or in several smaller ones of equal total area (Primack, 2006). The proponents of large parks argued that only large reserves had sufficient numbers of large, wide-ranging, low-density species (such as large carnivores) to assure the persistence of their populations. It was also argued that large reserves minimize the edge-to-area ratio, encompass more species, and can have greater habitat diversity than small reserves. Some evidence confirms some of these claims. In a study of mammal populations in 14 national parks of Western North America, local extinction rates were very low or zero in parks over 1000 km2 and much higher in parks smaller than that (Newmark, 1995). It is also true that human population densities are lower on the edge of large reserves compared with those on the edge of small reserves. This could contribute to the higher extinction rates in small parks (Parks and Harcourt, 2002; Wiersma et al., 2004).

On the other hand, once a park reaches a certain size, the number of new species added with each increase starts to decline. At that point, creating a second large park, as well as a third or fourth park some distance away, may be an effective strategy for conserving additional species (Primack, 2006). Some proponents of large reserves argued that small reserves need not be maintained, because their inability to support long-term population, ecosystem processes and all stages of ecological succession gave them little value for conservation purposes. Other conservation biologists argued that well-placed small reserves are able to include a greater diversity of habitat types and more populations of rare species than one large block of equivalent area (Shafer, 1995; Simberloff and Gotelli, 1984). Small reserves are particularly important for the protection of many species of plants, invertebrates and small vertebrates (Schwartz, 1999). The value of several well-placed reserves in different habitats was demonstrated by a comparison of four national parks in the United States (Primack, 2006). The total number of large mammalian species in three parks located in contrasting habitats is greater than the number of species in the largest US park, Yellowstone, even though the area of Yellowstone is larger than the combined area of the other three parks. Creating more reserves, even small ones, decreases the chance of a single catastrophic event – such as an invasive species, a disease or fire – destroying an entire species (Primack, 2006).

It has been argued the debate was a product of the island-biogeographic foundation of reserve design theory and ended in the inconclusive answer “it depends” (Possingham et al., 2000). Importantly, the island biogeography approach makes the assumption, which is often invalid, that reserves are habitat islands completely isolated by an unprotected matrix of inhospitable terrain. In fact, many species are capable of living in and dispersing through this habitat matrix (Primack, 2006).

Despite giving some insights into reserve design, the guidelines provided by island bio-geography offer little explicit guidance for decision-makers who are faced with specific choices about how many, which sites or which spatial configuration to include in a reserve network. For these reasons, reserve selection shifted its focus to systematic conservation planning, with its emphasis on quantitative targets, representativeness and efficiency (Margules and Pressey, 2000). The quantitative targets for species (or any other biodiversity feature) representation are often called representation targets. These can be the number of occurrences of a feature (e.g. a species) required in a reserve or the fraction of its total area of occurrence (e.g. a vegetation type) that must be included.

2.2. Formalization of conservation problems

In order to properly design and implement software planning tools, it is important to precisely specify both the problems to be solved and the algorithms to solve them. The formal problems relevant to reserve selection have been studied for a long time within computer science and operations research (Cerdeira and Pinto, 2005; Daskin, 1983; Hoffman and Padberg, 2001; Krarup and Pruzan, 1983; Paschos, 1997).

2.2.1. Constrained optimization

Problems solved by reserve selection tools can usually be formalized as constrained optimization (maximization or minimization) problems (Sarkar et al., 2006). One standard problem is to find the smallest set of sites such that all the representation targets are met. The quantity being optimized (minimized) is the number of sites; the constraint is that all the targets must be met. Formulating problems as constrained optimization problems is useful because a range of algorithms with known performance are available for solving them.

2.2.2. Reserve network selection problems

Numerous optimization problems can be formulated as mathematical programming problems (Cocks and Baird, 1989). A family of problems that occur in the design of reserve networks are variants of the “set cover” (also known as minimum set) and “maximal cover” (also known as maximum coverage) problems studied in operations research (Camm et al., 2002; Church et al., 1996; Possingham et al., 2000; ReVelle et al., 2002; Sarkar et al., 2006). The basic inputs of these problems are a set of sites constituting a planning region and a list of the conservation features occurring in each site. In the set cover problem, the goal is to minimize the total cost of the selected sites, while meeting a set of representation targets for the features. In a more formal formulation, let *m* be the total number of sites and *n* the number of different conservation features (e.g. species, vegetation types). Each site i has a cost c_i and each feature j has a target r_j. The variable x_i equals 1 if site i is selected, otherwise it equals 0. The contribution to the conservation of feature j by the selection of site i is contained in a matrix with elements a_{ij}. The objective is to minimize the cost:

$$\sum_{i=1}^{m} x_i c_i$$

subject to the constraint that the representation targets are met:

$$\sum_{i=1}^{m} a_{ij} x_i \geq r_j, for\ j = 1, \ldots, n$$

The “set cover” problem may assume simple or complex forms. Every site might be assumed to have the same cost, in which case the objective is to minimize the number of sites selected, or the cost can reflect actual monetary, management and/or opportunity costs. Each feature may be described in similar or different units (e.g., number of individuals, extent of occurrence, probability of occurrence) and individual targets can be set for each feature (Wilson et al., 2009b).

In the “maximal cover” problem, the objective is to maximize some measure of benefit, subject to a limit on the resources that can be expended (Wilson et al., 2009b). In a simple case, the measure of benefit might be the number of features that meet their targets, and the limit may be set for the number of sites that can be selected. Formally, the objective is to maximize

$$\sum_{j \in J} f\left(y_j(x.)\right)$$

subject to

$$\sum_{i \in I} c_i x_i \leq b$$

where c_i and x_i are as previously defined, and y_j is the amount of feature j conserved in reserve system $x.$, and f is a function that turns that into a value. The maximum available budget is b, which is in the same units as c_i. As in the set cover problem, there are multiple versions of the maximal cover problem. The “maximal cover” problem can be solved without using targets and the budget may or may not be sufficient for meeting all targets and may be updated through time if more or fewer funds become available. In the simplest case, if the target for feature j is achieved, y_j equals 1, otherwise it equals 0. Alternatively, the benefit can be measured by a set of functions representing the incremental gains in the conservation of each feature per dollar invested. These functions can be linear, meaning the benefits are proportional to the amount invested, or curved, to represent situations where there are diminishing or increasing benefits for each dollar invested. Features may be differentially weighted to emphasize investment in those that are of higher conservation concern, such as rare, endemic or threatened species (Arponen et al., 2007).

The basic versions of both problems can be represented as deterministic integer programming problems (Sarkar et al., 2004). Other goals can be incorporated as further constraints, such as shape (perimeter-to-area ratio) or the minimum size of clusters (contiguous sets of selected sites) (ReVelle et al., 2002; Rodrigues et al., 2000).

2.2.3. Multicriteria analysis

The allocation of land for biodiversity conservation frequently competes with alternative uses, such as agriculture, forestry, extractive activities, urbanization and recreation. Ignoring these alternative claims on land results in political problems and possible failure of conservation plans (Pierce et al., 2005; Sarkar et al., 2006). Therefore, effective conservation planning must take political and socioeconomic factors into account (Possingham & Stewart 2005; Knight et al. 2006; Lagabrielle et al. 2010). These can be integrated into reserve selection by using multicriteria analysis. Multicriteria analysis also allows for the incorporation of criteria relevant to the spatial configuration of the reserve networks, such as size, shape, replication, connectivity and dispersion, which play a determining role in the persistence of biodiversity (Margules and Pressey, 2000).

There are two types of protocols for incorporating multiple criteria into reserve selection, referred to as iterative stage protocols and terminal stage protocols (Sarkar et al., 2006). In iterative stage protocols, multiple criteria are considered as each site (or small set of sites) is selected for inclusion. One notable example is Marxan (Ball et al., 2009), which incorporates relevant criteria in its objective function. In the second type, terminal stage protocols, sets of potential reserve networks are identified on the basis of a given criterion, usually biodiversity representation, and further socioeconomic criteria are then used to select one of the potential reserves. ConsNet (Ciarleglio et al., 2009) is an example of a conservation planning tool that employs a terminal stage protocol. Both types can be used simultaneously, with some criteria incorporated during site selection and some at the end. Moffett and Sarkar (2006) noted that existing planning tools only incorporate a small fraction of the techniques available for multicriteria analysis.

2.2.4. Probabilistic data

Traditionally, reserve selection algorithms were used with distributional data that showed whether a feature was present or absent and, occasionally, its abundance or extent. A common issue is that frequently the available information consists on presence-only, and not presence-absence data. One way to minimize the problems caused by presence-only data is to model the potential distribution of features (e.g., species) in the planning region (Elith et al., 2006; Guisan and Zimmermann, 2000). Species distribution models (SDM) seek to quantify the relationship between species and their environment (Elith and Leathwick, 2009). They have been used to identify the main environmental variables that influence species' distributions (Guisan and Thuiller, 2005) and to predict their potential distributions under current conditions and future environmental change (Thuiller, 2004).Typical outputs consist of probabilities of occurrence of species for each site (Cabeza et al., 2004; Elith and Leathwick, 2009; Guisan and Thuiller, 2005; Phillips and Dudík, 2008).

Probabilistic data can be converted into binary (presence-absence) data by using a threshold probability (Carvalho et al., 2010). However, this procedure has been criticized because the choice of the threshold is arbitrary (Sarkar et al., 2004). There are two different strategies to use probabilistic data directly (Sarkar et al., 2006). In the first strategy, occurrence probabilities in individual sites are compounded to obtain the corresponding probabilities for the entire region. The objective then is to ensure the probability in the reserve network is higher than a specified valued, similar to a representation target. Although frequently adopted, this strategy assumes the independence of the probabilities of different features in the same site and of the same feature in different sites. Due to the ecological relationships between features and to the spatial autocorrelation of their distributions (Koenig, 1999), these assumptions are unrealistic. In the second strategy, the probabilities are interpreted as expectations (or expected numbers of occurrences) of the conservation features in sites. The expected values of occurrences can be summed across the whole area without assumptions of independence (Sarkar et al., 2004). In this case, the goal is that the expected total number of occurrences has to be higher than a representation target, just like with binary data. Simultaneous use of both probabilistic and binary data doesn't present a problem.

2.3. Algorithms and software

When designing algorithms to be incorporated in software tools, the main concern is with computational efficiency (or speed). For a better understanding of these issues, we introduce relevant terminology from computer science.

2.3.1. Computational complexity

Computational complexity is an attribute of a computational problem or algorithm and can be either a) temporal complexity, or the time required for a computation, with complexity being the inverse of efficiency; or b) spatial complexity, or the amount of memory necessary for a computation (Sarkar et al., 2006).

Regarding temporal complexity, a computational problem is said to belong to class P (for polynomial time) if the number of elementary operations (additions, subtractions, multiplications and divisions) required to *obtain an answer* increases as a polynomial function of the size of the input (preferably a low-order polynomial). The important thing here is that such algorithms are tractable, i.e. the time required to execute them (a polynomial function) does not grow inordinately fast as the size of the problem increases, compared to an algorithm that grows at an exponential rate. Problems are said to belong to class NP (for non-deterministic polynomial time) if the number of operations required to *verify a solution* grows as a polynomial function of the size of the input (Cormen et al., 2001). The contrast here is between the time required to produce a solution (for P problems) and that required to verify if a solution is correct (in the case of NP). P is at least a subclass of NP. One of the most important open problems in computer science is whether P = NP.

Given these definitions, a problem is said to be NP-complete if a) it is in NP and b) every other problem in NP is reducible to it, i.e. any such problem can be transformed into the NP-complete problem using a P algorithm. NP-complete problems are the hardest problems in NP. Finally, an NP-hard problem is one that satisfies clause (b) above but not (a); that is, it isn't necessarily in NP. Thus, NP-hard problems are at least as hard as NP-complete problems, possibly harder. The most important aspect of NP-complete and NP-hard problems is that increasing the speed of computer processors does not significantly alter the tractability of these problems (Garey and Johnson, 1979). However, this doesn't mean that every or even most instances of these problems cannot be solved efficiently. All it means is that there are instances for which a solution cannot be obtained in a reasonable amount of time, which represents an important restriction if the objective is to design generic software tools (Sarkar et al., 2006).

2.3.2. Heuristic algorithms

In reserve network design, both the set cover and maximal cover problems are NP-hard (Camm et al., 2002). Thus, exact or optimal algorithms, which are guaranteed to produce the optimal solutions (i.e. the most economical), may be intractable in many instances. However, for presence-absence data, the function to optimize can be linearized, reducing temporal complexity. For probabilistic data, some problems can also be represented linearly (Camm et al., 2002; Sarkar et al., 2004). Nevertheless, because even the linearized problems are NP-hard, it is important to develop efficient heuristic algorithms (or heuristics).

A number of stepwise or “single pass” heuristics have been devised. A stepwise algorithm consists of a rule (or a series of rules), according to which potential sites are ranked and the highest-ranking site is selected. The remaining sites are ranked again and the process is repeated until termination. Despite being efficient due to the simplicity of the rules incorporated in them, most of these heuristics were developed with spatial economy and transparency in mind, the latter being achieved through the inclusion of biologically relevant criteria, such as complementarity, rarity and adjacency (Sarkar et al., 2006).

The heuristic rules most frequently used for the selection of reserves are a) to maximize complementarity of conservation features (“complementarity rule”) and b) to maximize rarity of the features in a site, with rarity defined as the inverse of the frequency or extent of occurrence of a feature (“rarity rule”). Multiple tests on a variety of artificial and empirical data have shown that, for binary data, using both rules produces the best results (Csuti et al., 1997; Sarkar et al., 2002). For probabilistic data, it is best to use the complementarity rule (Sarkar et al., 2004). This rule has been incorporated in various planning tools such as C-Plan (Pressey et al., 2009) and WorldMap (Vane-Wright et al., 1991; Williams, 2001). ResNet (Kelley et al., 2002; Sarkar et al., 2002) incorporates both rules.

Stepwise heuristic rules are implemented in a hierarchic fashion. In case one of the rules leads to a tie between two or more sites for inclusion, a second rule is used, and this process is repeated for the set of rules. For instance, if rarity causes a tie, an adjacency rule, which gives preference to sites adjacent to one already selected, can be used to try to break the tie. The use of an adjacency rule leads to the selection of larger clusters (Nicholls and Margules, 1993). In this way, hierarchical rules allow an intuitive incorporation of multiple criteria. However, the relative importance the rules is determined by their sequence, with frequency of rule use largely determined by the number of ties. This can lead to weightings of the rules that are not explicit (Sarkar et al., 2006).

A more recent and sophisticated use of heuristics can be found in the Zonation prioritization software (Moilanen, 2007; Moilanen et al., 2005). The Zonation algorithm starts from the selection of the whole planning region, and iteratively removes the site that causes the smallest marginal loss of conservation value. Because Zonation does not aim to achieve specific representation targets, this process is repeated for every site, thus producing a hierarchy of conservation priorities for the entire landscape. The critical part of the algorithm is the definition of marginal loss (called the cell-removal rule), which also allows species weighting and species-specific connectivity considerations to be applied. Different cell-removal rules can be applied to emphasize different objectives, such as the retention of high-quality core areas for all species (Core-area Zonation), high average representation, at the cost of potential poor representation of some species (additive benefit function variant), or even target-based planning (through a special formulation of benefit functions) (Moilanen, 2007).

2.3.3. Metaheuristic algorithms

Before defining the term "metaheuristic", it is useful to introduce some terminology from mathematical optimization. For constrained optimization problems, a *feasible solution* is any solution that satisfies all the constraints. The set of all feasible solutions for a problem is called the feasible region, or *search space*. A solution is called a *local optimum* if all neighbouring solutions are worse than it. It is analogous to a local maximum (minimum) of a function. The *global optimum* is the best solution from among all feasible solutions. In the set cover problem, it is the set of sites which satisfy the representation targets for the least possible cost. In the maximal cover problem it is the set of sites that satisfies targets for the highest number of features, subject to a given cost limit. The global optimum is analogous to a global maximum (minimum) of a function.

With these definitions in mind, we can define a metaheuristic algorithm (or simply metaheuristic) as an algorithm that repeatedly uses a set of heuristic rules to explore the search space and escape from local optima (Illoldi-Rangel et al., 2012). Contrary to exact algorithms, metaheuristics are not guaranteed to produce optimal solutions. However, they provide an efficient method for producing good or near-optimal solutions. Metaheuristic algorithms can be used to incorporate multiple criteria. For example, an initial selection of sites can be followed by repeated random substitution of sites to find out if a better spatial arrangement can be achieved without sacrificing representation targets (Sarkar et al., 2006). Termination of the algorithm can be imposed by stipulating a limit to the number of iterations or the running time. For the selection of reserve networks, metaheuristics allow for a greater spatial economy than heuristic algorithms, at an acceptable decrease in computational efficiency. Additionally, they can produce many good solutions, whereas heuristic algorithms produce a single solution.

Although a wide range of metaheuristic algorithms have been developed (Gendreau and Potvin, 2010), most of them are yet to be used in conservation planning (Sarkar et al., 2006). Two metaheuristics have received particular attention for reserve network selection – simulated annealing (Kirkpatrick et al., 1983) and tabu search (Glover and Laguna, 1997). Both algorithms are described in more detail in the Marxan and ConsNet sections. Simulated annealing has been widely used, especially as implemented in the Marxan software package (Ball et al., 2009). It incorporates spatial criteria through inclusion of a boundary length penalty in its objective function. Tabu search, another metaheuristic algorithm, has recently been implemented in the ConsNet software package (Ciarleglio et al., 2009), although it had been successfully applied before (Sarkar et al., 2006).

2.3.4. Optimal algorithms

Optimal algorithms are designed to always find the global optimum; therefore, they generally achieve better spatial economy than heuristic and metaheuristic algorithms. However, due to the NP-hardness of conservation planning problems, they may take inordinate amounts of time to resolve realistically sized datasets (Sarkar et al., 2006). The most commonly used optimal method for solving reserve selection problems is the branch-and-bound algorithm (Csuti et al., 1997; Possingham et al., 2000; Sarkar et al., 2004). The efficiency and economy of stepwise heuristic algorithms, relative to optimal algorithms, has been analysed by several studies (Csuti et al., 1997; Mcdonnell et al., 2002; Pressey et al., 1997; Rodrigues and Gaston, 2002; Sarkar et al., 2004). These studies have generally shown that optimal algorithms, compared to heuristics, attain a minor increase in economy, with a considerable loss of computational efficiency and transparency (Sarkar et al., 2006).

2.4. Marxan and Simulated Annealing

Marxan is a free conservation planning software tool used to solve the set cover problem and some spatial extensions of it (Ball et al., 2009). It is the most widely used reserve selection software in the world, having been used by more than 2600 individuals from more than 110 countries (Watts et al., 2009). Marxan implements the simulated annealing metaheuristic algorithm, generating many good solutions to the set cover problem in a relatively short amount of time. Simulated annealing was chosen instead of other methods, because its authors considered it provided good answers quickly and was flexible, working well with problems of very different sizes and allowing the incorporation of complexities such as non-linearities. Besides minimizing the total cost of the reserve network, it can also be set to minimize the boundary length of the network, allowing it to select more compact reserve systems. In addition to normal representation targets, more advanced target options can be configured, such as minimum clump sizes and replication targets. These are discussed below.

Marxan solves an explicit and well defined mathematical problem, ensuring there is no ambiguity about what the algorithm is trying to achieve. The goal of this problem is to minimize a combination of the cost and boundary length of the reserve system, whilst meeting a set of representation targets. The optimization problem for which Marxan finds good solutions is:

$$minimize \sum_{i}^{N_s} x_i c_i + b \sum_{i}^{N_s} \sum_{h}^{N_s} x_i (1 - x_h)\, cv_{ih}$$

subject to the constraint that all the representation targets are met

$$\sum_{i}^{N_f} x_i r_{ij} \geq T_j \forall\, j$$

and x_i is either 0 or 1

$$x_i \in \{0,1\} \;\forall\; i$$

where $r_{ij}$is the occurrence level of feature j in site i, c_i is the cost of site i, N_s is the number of sites, N_f is the number of features, and T_j is the target level for feature j.

The control variable x_i has value 1 for sites selected for the reserve network and value 0 for sites not selected. The first term in equation 2.1 represents the total cost of the reserve system. The second term, in its most common use, represents the boundary length of the system multiplied by the boundary length modifier, b. This parameter determines how high the penalty for boundary length is relative to the cost of the selected sites. The higher the boundary length modifier (BLM), the more emphasis the algorithm will put into generating compact networks. The effect of increasing the BLM is illustrated in Figure 3. When the BLM is set to 0, there is no requirement for spatial compactness, and the algorithm focuses only on minimizing the costs. Thus, the resulting solution (in purple) has a smaller total area but is highly fragmented. When the BLM is increased to a value greater than 0, the requirement for spatial compactness results in sites being clumped together. The resulting solution (in yellow) is spatially compact.

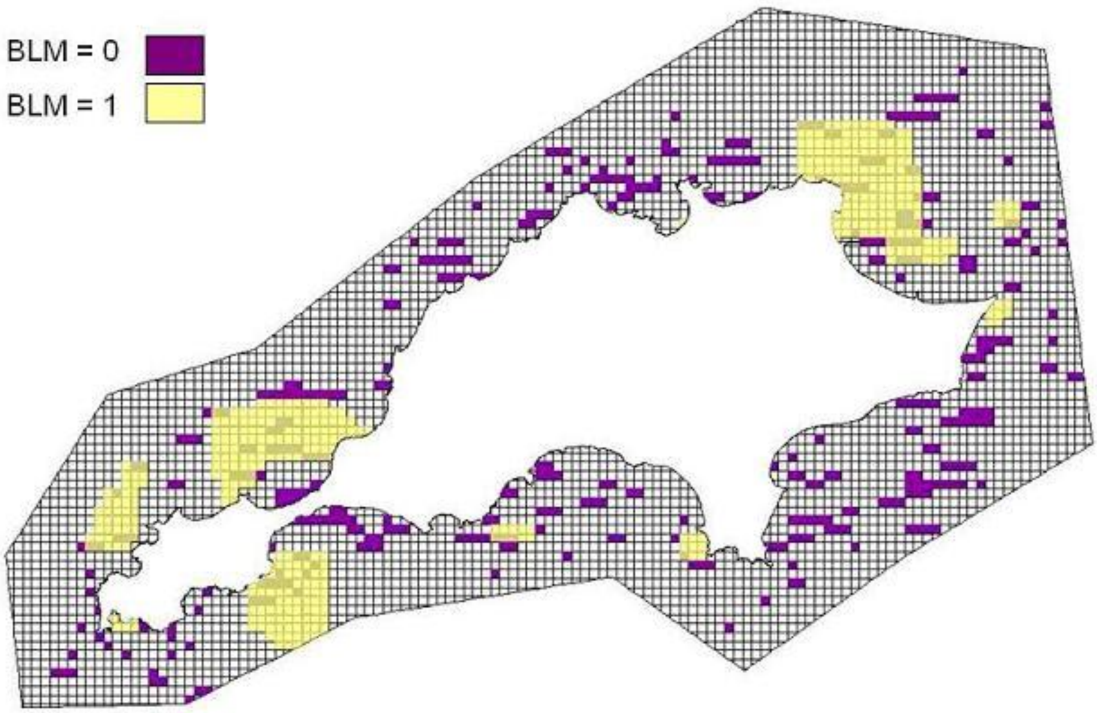

Figure 3. Effect of BLM on the spatial configuration of the reserve network. A BLM of 0 results in a highly fragmented solution (in purple), albeit with smaller total area. A BLM of 1 produces a much more compact solution (in yellow), at the expense of a larger total area.

The connectivity matrix, with elements cv_{ih}, usually contains the length of the boundary of each site with sites adjacent to it. If one site is included in the reserve system, and an adjacent site is not, the "connection cost" (whose magnitude is determined by the BLM) must be paid. If both sites are in or out, the cost is not paid. While cv_{ih} is usually set to be the boundary length, it can also be used more innovatively. For instance, it could be a quantitative measure of flow of propagules from sites i to h, where the sites may be separated by some distance. In this case, Marxan will look for solutions that maximize the tendency for propagules generated in the network to be retained in the network. The use of a connectivity matrix allows connections between sites that are not adjacent. Thus, it allows us to introduce a cost (or benefit) for including a particular site and any other site to which that particular site is connected (Ball et al., 2009).

The representation targets can be the number of occurrences of a feature (e.g., 15 populations of one species) or a proportion of it (e.g., 30% of the extent of a habitat). The target value is expressed in the same units used to define the amount of each feature in each site. A number of advanced target options may be set as well; these include the minimum clump size, replication target and target for number of sites.

When the amount of a feature in a set of contiguous sites (i.e., a cluster or “clump”) is less than the predefined *minimum clump size*, those occurrences do not count towards meeting the representation targets for that feature. This is useful when small or isolated patches or populations are of lower conservation value than larger, well-connected ones.

When using abundance or probabilistic data, one can also set the *minimum number of cells* the feature must occur in for a viable reserve selection. This value may be used in situations where, even though the representation target may be met in just one cell, one would like that feature to be represented in a greater number of cells (e.g., for risk spreading). This target isn’t expressed in the units used to describe the occurrence of conservation features; it is simply the number of cells the features must occur in.

We can also set *replication targets*, i.e. the number of separated occurrences of a feature required in the reserve system. Along with this target, users specify the *minimum separation distance*, i.e. the minimum distance at which cells holding a feature are considered to be separate. This may be useful in situations where multiple occurrences are desired and should be separated by a given distance.

The use of minimum clump sizes and replication targets significantly slows down Marxan if the number of cells is in the high thousands or greater, therefore the authors recommend running the software first without these features, and only using them if adequate solutions aren’t found.

It is important to note that targets in Marxan are specific to the conservation features and not for spatial characteristics, such as the minimum size of areas or the number of distinct areas zoned for conservation.

In order for the simulated annealing algorithm to work, it needs an objective function which can be evaluated. Marxan solves this problem by combining equations 2.1 and 2.2 into an objective function, transforming the constraints into an additional penalty term. This means that a solution which does not meet all of its conservation targets can still be given a value, which is of practical use in the annealing process. In words, the objective function is as follows:

Score = **Cost** of the reserve system + (**BLM** x **Boundary length** of the reserve system) + (**SPF** x **Penalty** incurred for unmet targets)

For each alternative solution, Marxan calculates whether the target for each conservation feature is met or not. If a target is unmet, then a user-defined penalty cost – called the Species Penalty Factor or SPF – is applied. Since the SPF is user-defined, different weighting can be given to different feature targets. The same SPF can be applied to all conservation features, but an individual calibration allows the algorithm to explore more configurations and potentially find more efficient (in the sense of having a lower cost) solutions (Ardron et al., 2010).

Marxan seeks to minimise the objective function score, because the lower the score, the more efficient the solution. To do this while avoiding getting trapped in local optima, simulated annealing combines iterative improvement with occasional random increases in cost. A more detailed description of simulated annealing is provided next.

2.4.1. Simulated Annealing and its implementation in Marxan

Simulated annealing (Kirkpatrick et al., 1983) is an optimization metaheuristic based on the annealing process in metallurgy, in which a metal is heated and then slowly cooled to a crystalline state with minimum energy and larger crystal size in order to reduce its defects. The annealing process involves carefully controlling the temperature and cooling rate. The concept of slow cooling is implemented in simulated annealing as a slow decrease in the probability of accepting worse solutions as it explores the search space.

In a minimization problem any moves (or changes) that decrease the value of the objective function f will be accepted, however, some changes that increase f will also be accepted with a probability p, also called the transition probability. In its simplest form this probability is given by

$$p = e^{-\frac{\delta f}{T}}$$

where δf is the change in the objective function value and T is a parameter called temperature (Yang, 2008). Whether or not a change is accepted is usually determined by comparing the expression above with a randomly generated number r. Thus, if $p < r$, the change is accepted, otherwise it is rejected.

In Marxan, the simulated annealing algorithm will run for a user-defined number of iterations. An initial potential solution is created either from a user-defined starting point (e.g., the existing protected area network) or from a randomly selected fraction of cells (which might be all or none of them). The objective function value of this solution is evaluated. New trial solutions are generated iteratively by randomly changing the status of a single panning unit (i.e. adding or removing one cell) and assessing the objective function value of the new configuration. If this value improves (decreases), the change is accepted; if the value increases, the change may or may not be rejected, depending on the current temperature T and on the size of the increase in cost δf. The temperature starts at a high value and decreases during the algorithm. When the temperature is high, almost all changes (either good or bad) are accepted. As the temperature decreases, the chance of accepting a bad change decreases, especially if that change increases the score by a large amount (large δf) . By the end of a simulated annealing run, only changes that improve the score are accepted (Possingham et al., 2000).

Two types of simulated annealing can be used in Marxan (Game and Grantham, 2008). One is “fixed schedule annealing” in which the annealing schedule (initial temperature and rate of temperature decrease) is defined by the user before the algorithm initiates. The second is “adaptive schedule annealing” in which Marxan samples the problem and sets the initial temperature and cooling rate based upon its sampling.

2.4.2. Marxan user interface

Standalone Marxan uses a simple command line interface. However, it can also be used as a plug-in for a number of decision support tools such as C-Plan, CLUZ, PANDA and NatureServe Vista. These tools provide graphical outputs, and some allow easy creation and manipulation of input files.

2.4.2.1. Input Files

The input files are all simple comma- or tab-delimited text files, but some usually require the use of a Geographical Information System (GIS) such as ArcGIS or Quantum GIS to build them. The required input files are: the *Input Parameter File*, the *Conservation Feature File*, the *Planning Unit File* and the *Planning Unit versus Conservation Feature File*. The Input Parameter File is used to define many of the parameters that determine Marxan function, such as the BLM value, as well as to specify the location of the other input files and the output directory. The Conservation Feature File lists the IDs of the conservation features, their names, targets and their species penalty factor. The Planning Unit File contains the ID of every cell of the planning region, the cost of each cell and its status (included, not included, permanently included, and permanently excluded). Finally, the Planning Unit versus Conservation Feature File contains the amount of each conservation feature in the cells the features occurs in. Additionally, the user can create two optional files: the *Boundary Length File* and the *Block Definition File*. The Boundary Length File contains information about the length (or other measure of connectivity) of shared boundaries between cells. This file is required if one wants to generate solutions using the BLM feature. The Block Definition File is similar to the Conservation Feature File, allowing the user to set variable values, such as targets, for groups of conservation features (these groups may be defined in the conservation feature file). It is also using this file that the user can set a proportional target for features by simply writing the proportion, instead of having to calculate it manually or using a spreadsheet.

2.4.2.2. Output files

When generating solutions with Marxan, the user sets a number of runs (typically 100), each of which will generate a solution. There are two standard Marxan outputs. The *Best Solution File* lists the reserve network with the lowest objective function score from among all the runs. It consists of a list with all the cell IDs in the first column and either a 1 or a 0 in the second column, indicating whether that cell was selected or not. The *Summed Solution File* records the selection frequency of the cells across all the runs. For instance, a cell that is selected in all 100 runs will have a selection frequency of 100, while one that is selected in only half the runs will have a selection frequency of 50. The selection frequency of a cell is a measure of how important that cell is to meeting the representation target. A selection frequency map shows which areas are more often included in solutions and which are not. This is frequently used as an indicator of the irreplaceability of a site. Cells will have a low selection frequency if there are a variety of equally good alternatives. If they are strictly irreplaceable, they will be selected in every solution. An illustration of how selection frequency works is provided in Figure 4.

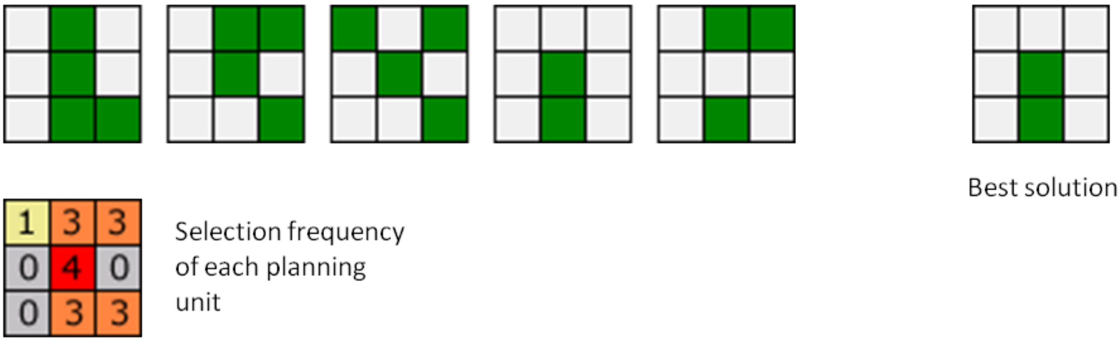

Figure 4. Example outputs from 5 runs of Marxan on a dataset with 9 cells. The first five grids represent the solution for each run. The grid labelled "Best solution" corresponds to the solution with the fewest cells. The bottom grid displays the selection frequency of each cell, i.e. the number of times each cell was selected across the 5 runs. The higher this value, the more important that cell is for achieving the representation targets efficiently.

The other output files available are: 1) the solution for each run, 2) missing value information for each run (or for the best run only), 3) summary information, 4) scenario details, 5) screen log file, and 6) snapshot files. The solutions for each run have the same format as the Best Solution File. The missing values files contain information about the representation targets and achievements for each feature. The summary information file contains information for each run such as the objective function score, cost, number of cells, boundary length and how many species haven't met their target. The scenario details file is a list of the main parameter values for that scenario, such as the BLM value, the number of iterations and runs and the simulated annealing parameters. The screen log file contains exactly what the Marxan command line interface displayed as screen output for that scenario. Finally, snapshot files present the solution progress at stages during the optimisation procedure. The current solution is saved either at a predetermined interval of iterations or system changes. It is saved in the same format as the final solution for each run. These files allow the user to examine the progress of a solution method and are generally not recommended, since they are only needed for advanced analyses to look at how the annealing proceeds under different parameter values. The output files to be generated by Marxan are specified by the user in the Input Parameter File.

2.5. Marxan with Zones

An important limitation of most conservation planning tools, including Marxan, is their inability to simultaneously consider multiple types of zones to reflect the variety of management actions being considered in a conservation plan. Marxan with Zones (Watts et al., 2009) fills this gap, allowing any cell to be allocated to a specific zone, not simply reserved or unreserved, as with standard Marxan. Marxan with Zones assigns cells to a particular zone while meeting representation targets at a minimum total cost. For instance, it can be used to design marine protected areas with different levels of protection or terrestrial conservation area networks with different conservation actions. Although it has many advantages, Marxan with Zones requires a lot of additional data, such as the cost of placing a cell into any one of the different zones, the benefit to each conservation feature of being placed into a particular zone, and the relative merits of having each zone type juxtaposed with another zone type. This latter concept can be used to create a zoning map where highly protected areas can be buffered by less protected areas.

2.6. Zonae Cogito

Zonae Cogito (ZC) is a decision support tool developed by the authors of Marxan (Segan et al., 2011). It works as a graphical user interface for Marxan and Marxan with Zones, and incorporates the MapWindow GIS. Zonae Cogito allows users to edit input files and parameters of Marxan and to convert some GIS-generated data into Marxan-compatible files. However, an external GIS is still necessary to perform the spatial calculations required to generate some Marxan input files. Users can run Marxan from within ZC, and modify and refine the networks identified in Marxan according to their needs and preferences. An important stage in any Marxan analysis is calibration of key parameters, such as the species penalty factor, the boundary length modifier and the number of iterations. Traditionally, calibration requires editing the parameters in the input text files, rerunning Marxan, and then visually analysing the output, which might include visually inspecting it in a GIS. This routine operation is laborious, time-consuming and typically requires two or three different software applications to complete (the Marxan executable, a spreadsheet program and a GIS). Zonae Cogito automates this process: the user is only required to select a parameter to be calibrated and the range of values to be explored; ZC then runs Marxan with the different values and summarizes the results in a table. These results can then be graphed to bar and scatter plot graphs. Bar graphs can be used to compare solutions based on cost, boundary length and target achievement. The scatter plots are very useful for calibration. For instance, ZC can plot boundary length against cost for various values of the BLM, a common method used for calibrating this parameter (Figure 5). Zonae Cogito also allows users to systematically explore the results of many Marxan runs using cluster analysis, the results of which can be visualized with dendrograms and non-metric multidimensional scaling plots.

Marxan, Marxan with Zones and Zonae Cogito are all free software and can be downloaded from the Marxan website (http://www.uq.edu.au/marxan/), along with their user manuals and the Marxan Good Practices Handbook.

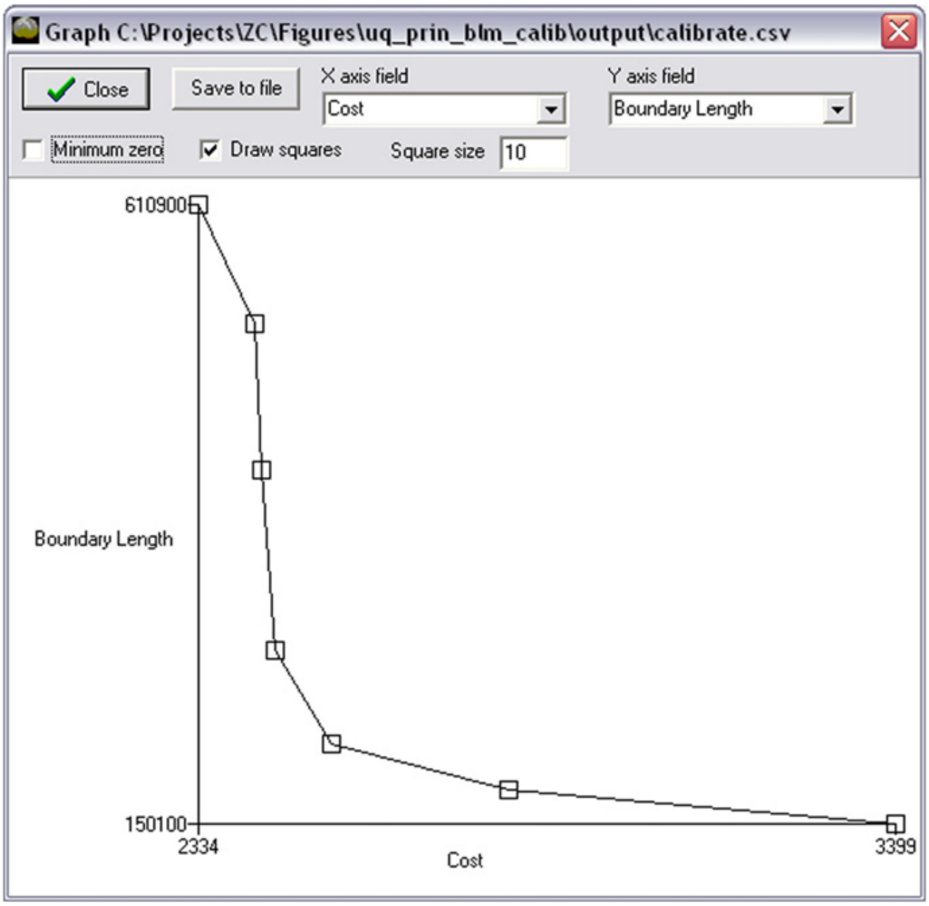

Figure 5. Screenshot of the Zonae Cogito graphing functionality. Here a tradeoff curve has been plotted between boundary length and cost, a common approach to calibrating the BLM parameter in Marxan.

2.7. ConsNet and Tabu Search

ConsNet is a software package for the selection of reserve networks, designed to solve the set cover problem (Ciarleglio et al., 2009). The most recent version can also solve the maximal cover problem. It is able to incorporate diverse spatial criteria in its analysis, including compactness, connectivity and replication, as well as an arbitrary number of user-defined costs, reflecting socio-economic or other criteria. ConsNet is built on the modular adaptive self-learning tabu search (MASTS) framework (Ciarleglio, 2008), and incorporates a number of advanced techniques, such as adaptive tabu search, dynamic neighbourhood selection and rule-based objectives.

The ConsNet authors formulate the set cover problem slightly differently from the Marxan authors: the usual objective of minimizing the total cost of selected sites is replaced by minimizing the number of selected sites (Ciarleglio et al., 2008). Both objectives are equivalent when the cost is equal for all sites. ConsNet focuses on multicriteria variants of this problem, attempting to minimize the number of selected sites while simultaneously optimizing a variety of costs and spatial criteria. In order to properly describe the advantages of the techniques used by ConsNet, we will first give a brief explanation of Tabu Search.

2.7.1. Tabu Search

Tabu search (Glover and Laguna, 1997) is a metaheuristic algorithm used to find solutions for optimization problems. Like simulated annealing, it is a local search algorithm, which means it starts with a potential solution and tries to improve on it by iteratively evaluating neighbouring solutions and selecting the best one. As previously mentioned, local search algorithms have a tendency to get stuck in local optima. Tabu search avoids this problem by using a list (called tabu list) of recently visited solutions, marking them as “tabu”, so that the algorithms is forbidden from repeatedly visiting them. In its simplest form, a tabu list is a short-term set of the solutions that have been visited in the recent past, that is, less than *n* iterations ago, where *n* is the number of previous solutions to be stored – *n* is also called the *tabu tenure*. Another common tabu restriction is that the search is not allowed to make moves which would undo a recent move. Starting from an incumbent solution, an iteration consists of the following steps: 1) select a neighbourhood, 2) evaluate neighbouring solutions, 3) select the best non-tabu solution as the new incumbent solution and 4) update the tabu memory structure.

2.7.2. ConsNet implementation of Tabu Search

The ConsNet search algorithm incorporates three advanced techniques: adaptive tabu search, dynamic neighbourhood selection (DNS) and rule-based objectives (RBOs).

The adaptive tabu search feature dynamically adjusts the tabu tenure based on the number of consecutive improving or disimproving moves that have recently been made. This feature improves performance and prevents the search from getting trapped in a local optimum (Ciarleglio et al., 2008).

In ConsNet, the fundamental move toggles the status of a single site, which creates a unique neighbouring solution by either adding or removing that site from the network. The traditional full neighbourhood would contain *n* neighbouring solutions, where *n* is the number of cells in a dataset. If *all n* neighbours were evaluated at each iteration, the search would be unreasonably slow. To overcome this problem, ConsNet reorganizes the full neighbourhood into smaller subsets, structured by geographical proximity. Each subset defines a smaller neighbourhood. Dynamic neighbourhood selection is a meta-strategy which manages multiple neighbourhoods and attempts to choose the best one for the next iteration in the search. ConsNet allows the user to select from four different neighbourhood selection strategies, each appropriate to different situations. A more detailed description of how DNS works can be found in Ciarleglio et al. (2008).

In contrast to Marxan (and simulated annealing in general), ConsNet does not use an objective function to evaluate alternative solutions. Instead, a binary comparison operator is used, that considers two different solutions and assesses if the first is superior, equivalent or inferior to the other. A rule based objective defines a hierarchical set of rules used to make these ordinal comparisons between two different solutions. These rules are defined according to the objectives created in the user interface of ConsNet. RBOs allow the user to incorporate multiple criteria in a disaggregate fashion, unlike objective functions, which often use a weighted composite of different attributes of the solution (as happens in Marxan). Thus, RBOs enable the search to incorporate precise ordinal rankings and may be more compatible with user preferences in some multicriteria analyses. The design and application of RBOs are covered in depth in Ciarleglio et al. (2008).

2.7.3. User interface and features

ConsNet can consider the following spatial attributes: shape, connectivity and replication. Shape is defined as the perimeter-to-area ratio of the reserve network. Connectivity is measured in ConsNet as the number of different clusters in the network. Replication is the number of clusters in which a conservation feature can be found.

Besides spatial criteria, ConsNet can also consider an arbitrary number of costs (or benefits) assigned for each cell.

Based on some or all of these spatial criteria and costs, a search objective is defined. Users can select one of the predefined objectives, which analyse either the minimum area or maximal cover problem. Alternatively, users can create their own multicriteria objectives using any of the above criteria.

ConsNet features a user-friendly graphical user interface (GUI), in which all of the work apart from the creation of the input files is done. Results are presented in the objectives tab as the search progresses, and can be sorted according to any of the criteria considered. The user can also enable the option to display real-time graphical output, in the form of maps. ConsNet can save all of the objectives, search progress and best solutions to the hard drive, so this information is available the next time the program is started.

The input data consists of text files, much like Marxan. The *Representation File* contains information on the amount of conservation features in cells, as well as the coordinates of and spacing between each cell (which allows the computation of the area and perimeter). ConsNet displays the cells in a regular grid based on the coordinates. The *Representation Targets File* is only necessary if there are different representation targets for each feature. If targets are expressed as a fraction of occurrences and are equal for all features, they can be set using the user interface. This file contains the representation targets for each feature. Multiple sets of targets may be defined i.e., the same feature can be given multiple targets. In the *Replication Goals File*, replication targets are set for each feature. Costs (either positive or negative) can be assigned to cells using the *Costs File*. Finally, the *Cells File* is used to provide ConsNet a list of cells. This file is required if the user wants to specify a list of permanently included (such as currently protected areas) or excluded (such as urban areas) cells. It is also used when importing a solution into ConsNet.

Although individual cells may possess any shape, ConsNet offers better performance and built-in visualization when the cells are arranged in a rectangular grid. If cells are not rectangular, the representation file has a different format.

Following the creation of input files, a step-by-step wizard facilitates the initial setup of a problem. A problem profile is automatically created and saved by ConsNet. This problem, and all information associated with it, such as its objectives and solutions, can be loaded the next time the program starts. Users can then run a number of very fast heuristic algorithms based on rarity and complementarity to generate potential solutions. This heuristics allow a quick initial assessment and can serve as a starting point for more in-depth searches using predefined or user-built objectives. After creating an objective, all of the heuristic solution can be evaluated and automatically ranked. Starting a search from a high quality heuristic solution can save a significant amount of time. A search can run for a user-defined number of iterations or seconds, or indefinitely until the stop button in the GUI is pressed. Advice on how long to run the search is given in the ConsNet user manual (Ciarleglio et al., 2010).

ConsNet can take advantage of multiple processors, such as dual core or quad core processors. Not only does it run a single search faster, but it can run multiple searches simultaneously. The number of searches is limited to the number of processors available. When working with large datasets, users can allocate more memory by running ConsNet on a 64-bit machine.

ConsNet and its user manual can be downloaded from:

http://uts.cc.utexas.edu/~consbio/Cons/consnet_home.html

Chapter 3. Comparing the Marxan and ConsNet reserve selection tools: a case study in northwest Iberian Peninsula

3.1. The BIODIV_GNP project

"BIODIV_GNP – Biodiversidad Vegetal Amenazada Galicia-Norte de Portugal. Conocer, gestionar e implicar" is a conservation project whose ultimate goal is to set the conservation priorities and coordinated management mechanisms for the territory of Galicia and Northern Portugal, in order to minimize the impacts and stop the loss of habitats and of threatened and/or endemic plant species, with the participation of the relevant stakeholders and on the basis of multidisciplinary scientific knowledge.

This project results from a collaboration between the following stakeholders:

- Universidade de Santiago de Compostela
- Faculdade de Ciências da Universidade do Porto
- Fundação Centro de Estudos Euro Regionais Galicia-Norte de Portugal
- Fundação Fernão Magalhães para o Desenvolvimento
- Dirécion Xeral De Conservación da Natureza | Xunta de Galicia

3.1.1. Area of incidence

This project comprises two types of geographic areas of intervention:

- Priority areas, which will be subject to all of the actions planned in this project: rural border areas of the neighbouring comarcas (Galicia) and distritos (Portugal) between Galicia and Northern Portugal.
    - Galicia: O Baixo Miño, Vigo, O Condado, A Paradanta, Terra de Celanova, Baixa Limia, A Limia, Verín and Viana.
    - Portugal: Viana do Castelo, Braga, Vila Real and Bragança.
- Extended areas, which will be subject to some of the actions planned in the project:
    - Galicia: Pontevedra, Ourense, A Coruña and Lugo.
    - Portugal: Minho, Douro Litoral and Trás os Montes.

3.1.2. Assessment and proposed expansion of the Protected Areas Network

The BIODIV project has twelve specific objectives, two of which are most relevant to this dissertation: 1) to assess the adequacy of current protected areas relative to the objectives of plant biodiversity conservation; and 2) to propose the expansion of the current protected areas network.

For the expansion of the current reserve network, it was decided that new areas should be preferably adjacent to the existing areas, so as to promote the connectivity of the resulting network, and that the representation targets should be met at the lowest possible cost. Because a cost surface wasn't available, area was chosen as the variable to minimize. Therefore, the proposed reserve network should be as small as possible, while achieving the representation targets and retaining connectivity.

3.2. Materials and Methods

3.2.1 Study area and physical data

The study area consists of the Galicia autonomous community and Northern Portugal region**.** It has rugged landscapes, consisting of low mountain ranges, generally below 1000 m, although some rise to 2000 m, in eastern Galicia and North-eastern Portugal. Galicia is known for its *rias*, estuaries drowned due to rising sea levels after the last ice ages. The south-eastern region of the study area has a warm-summer Mediterranean climate, with mild temperatures and occasional summer drought and wet winters. The western and northern coastal regions are characterized by their Atlantic climate, with more uniform precipitation patterns throughout the year and milder summers. In the eastern part of the border region, population densities are low and settlements are scattered. There, the economy is still heavily dependent on traditional agriculture, mainly in small landholdings. Some of the threatened plant biodiversity of Galicia and Northern Portugal is associated with traditional human land-use patterns, which generate a diversity of habitats. The rural abandonment that has occurred contributed to a homogenization of the landscape which may have reduced biodiversity. There are new risks associated with this process, such as an increase in wildfire frequency, causing destruction of habitat and soil loss (BIODIV_GNP, 2010). The study region is part of the Mediterranean biodiversity hotspot (Myers et al., 2000). It harbours numerous endemic species because it was one of the major glacial refugia in Europe during the Pleistocene (Comes, 2004; Médail and Diadema, 2009).

To define the cells we clipped the UTM 1x1 km grid by the study region limits, using ArcGIS (ESRI, 2011). Thus, our study area contains a total of 52,121 cells. Current protected areas spatial data was obtained from the Instituto da Conservação da Natureza e das Florestas website (http://www.icnf.pt/portal/naturaclas/cart/ap-rn-ramsar-pt) for Portugal and the Ministerio de Agricultura, Alimentación y Medio Ambiente website (http://www.magrama.gob.es/es/biodiversidad/temas/espacios-protegidos/) for Spain. The protected areas layer was overlapped with the study area layer and every cell that contained any percentage of protected area was considered as protected. Using this definition, a total of 13,218 cells divided among 75 separate areas comprised the protected areas network in the study area. The protected cells were locked in every solution in both Marxan and ConsNet. Cells with more than 50% of their area being urban were considered inadequate for reservation and excluded from consideration (Zhang et al., 2011). This way, 827 cells were locked out of solutions. This left 38,076 cells available for selection by the reserve design software.

3.2.2 Species distributional data

For this study we used data on 11 species of threatened and/or endemic flora, for which species distribution models were built as part of the BIODIV_GNP project. Even though the collection of occurrence records and the production of distribution models was not part of this dissertation, a short description of the process is described here to provide context.

A list of 153 species was assessed in the BIODIV_GNP project and 11 selected for modelling based on the set of known occurrences and their IUCN conservation status. Table 3.1 presents the plant species selected and the individual species conservation status, observed occurrences and predicted occurrences obtained from SDMs. To build the SDMs, an initial selection of environmental variables was done based on available literature and expert knowledge. Overall, the selected variables were considered to be the most likely to determine the distribution of the species. To avoid using correlated variables, only variables with a Spearman correlation coefficient below 0.7 were considered (Elith et al., 2006). As a result, a final set of 5 variables was used for model calibration: mean annual temperature, temperature seasonality, annual precipitation, number of distinct land covers per grid cell and the percentage cover of agricultural areas per grid cell. Species distribution models were calibrated using an ensemble forecasting method from the *biomod2* package (Thuiller et al., 2009), in the R statistical environment (R Development Core Team, 2012). Because occurrence records only contained information on species presence, a number of pseudo-absences equal to 2% of the study area were randomly generated (Barbet-Massin et al., 2012). Ten repetitions were used for model calibration. Predictions from the different techniques available in *biomod2* were used to create a single ensemble model, by using the average value of all the predictions. This consensus method, designated as *Mean (all)* by *biomod2*, was used because it provides more robust predictions than models calibrated using a single technique or other consensus methods (Marmion et al., 2009).

Table 1. Plant species used in the analysis, their conservation status and their observed and predicted occurrences.

Conservation status	Species	Observed occurrences	Predicted occurrences
Critically Endangered	*Eryngium viviparum* Gay	26	3360
	Genista ancistrocarpa Spach	25	3397
Endangered	*Armeria humilis* (Link) Schult *subsp. humilis*	31	818
	Armeria humilis subsp. odorata (Samp.) Pinto da Silva	45	3248
	Centaurea borjae Valdés Berm. & Rivas Goday	29	595
	Iris boissieri Henriq.	95	2679
Vulnerable	*Succisa pinnatifida* Lange	42	5504
	Veronica micrantha Hoffmanns. & Link	83	7848
Near Threatened	*Eryngium duriaei subsp. juresianum* (M. Laínz) M. Laínz	58	6445
Least Concern	*Narcissus cyclamineus* DC.	132	11657
	Santolina semidentata Hoffmanns. & Link	411	2838

3.2.3 Scenarios

In this study, a uniform cost layer was considered. Hence, each cell was assigned a cost of 1 unit. This was chosen so that both Marxan and ConsNet were solving the minimum area problem, i.e. trying to minimize the number of cells selected, subject to the constraint that all targets had to be achieved. We created six different target scenarios, according to the type of occurrence records used and whether conservation status was taken into account:

A. Equal targets for every species:
    1. 50% of observed occurrences, no target for predicted occurrences.
    2. 25% of predicted occurrences, no target for observed occurrences.
    3. Simultaneously 50% of observed occurrences and 25% of predicted occurrences.
B. Higher targets for endangered (EN) and critically endangered (CR) species:
    1. 75% of observed occurrences for CR and EN species, same as A1 for the rest.
    2. 50% of predicted occurrences for CR and EN species, same as A2 for the rest.
    3. Simultaneously 75% of observed occurrences and 50% of predicted occurrences, same as A3 for the rest.

In order to set simultaneous targets, observed occurrences and predicted occurrences for each species were represented in input files as different features. For instance, in scenario A3, we set a target of 50% of the *observed* occurrences of *Iris boissieri* and 25% of the *predicted* occurrences for that same species.

3.2.4 Marxan

For this study, we used Marxan v2.43 (Ball et al., 2009). As explained in Chapter 2, the Marxan algorithm should be carefully calibrated, to ensure its solutions are as close to the global optimum as possible. Failure to adequately calibrate the key Marxan parameters may result in inefficient solutions, an inappropriate level of clumping, unmet conservation targets or an inefficient running time. The key Marxan parameters to calibrate are 1) the conservation feature/species penalty factor (SPF), 2) the number of iterations and 3) the Boundary Length Modifier (BLM).

3.2.4.1. Species Penalty Factor Calibration

In this analysis, the SPF was calibrated first. This parameter is essential to get good results. If the SPF is too high, it restricts Marxan's performance and leads to fewer different solutions with higher average cost. If the SPF values are too low, representation targets may not be achieved. To calibrate the SPF, the last method described in Chapter 8 of the Marxan Good Practices Handbook was followed (Ardron et al., 2010). In this method, we find a uniform SPF for which all targets are met, then a lower value for which most of the targets are missed. We then start from this lower value and gradually increase the SPF only for the features missing their targets, until all targets are met. In this study, the lower values ranged from 0.001 to 0.01, while the upper values ranged from 0.01 to 0.5. The solutions generated by Marxan using individually calibrated SPF had a smaller area than the solutions with the higher uniform SPF, confirming the importance of adequately calibrating this parameter. The SPF was calibrated using 50 repetitions of 10^6 iterations each, as this was sufficient to determine if targets were being met.

3.2.4.2. Number of iterations

The number of iterations determines how close Marxan solutions will be to the global optimum. Generally, the more iterations are run, the more efficient the solutions will be. However, the processing time increases linearly with the number of iterations, so there are practical limits on the number of iterations that can be run. The recommended starting point for calibrating this parameter is 10^6 iterations (Ardron et al., 2010). We then increased this by a factor of 10, to 10^7 iterations, and checked whether the best solution had a lower objective function score. If it did, we further increased the number of iterations by a factor of 2, to $2x10^7$ iterations, and checked the score. If the score had improved (lowered) by more than 1 unit (corresponding to 1 cell), we increased the number of iterations by a factor of 2. This process was repeated until there was marginal to no improvement in the objective function score. The final number of iterations chosen for each scenario was the lowest value for which there was an improvement of more than 1 unit, relative to the previously tested value.

3.2.4.3. Boundary Length Modifier Calibration

The boundary length modifier controls the clustering and compactness of solutions. Since both Marxan and ConsNet are capable of optimising compactness in addition to cost, we decided test this capability. In Marxan, there is a clear trade-off between solution efficiency and boundary length. When the BLM is zero, the algorithm focuses exclusively on minimizing cost, while meeting representation targets. When the BLM is higher than zero, the boundary length is taken into consideration in the calculation of the objective function score. Higher BLM values lead to more compact solutions with generally higher cost. While the other parameters are being calibrated, it is advisable to leave the BLM set a 0 (Ardron et al., 2010), and that was the strategy followed in this study.

To calibrate the BLM, we used the method described by Fischer and Church (2005) and suggested in the Marxan Good Practices Handbook. This systematic method for varying BLM allows the user to quickly discover the range of BLM values that will make the largest differences in spatial patterns of solutions without having to guess at appropriate values. The first step of this method is to set the BLM to 0 and run Marxan to find the lowest cost solution possible. The cost and boundary length of that solution are annotated. The second step is to set the costs of every cell to 0 and the BLM to 1, and run Marxan to find the minimum possible boundary solution. The cost and boundary length of this solution are annotated as well. If plotted, this points look like the X and Y points of Figure 6. The third step is to calculate the slope of line “a” connecting these two solutions: (Cost(X) – Cost(Y)) / (Boundary(X)-Boundary(Y)). The absolute value of the slope is then used as the BLM and all costs are reset back to their original values, which in this case are 1 for all cells. Small changes in BLM around this value are likely to make the largest changes in spatial patterns of selected reserve networks. We ran Marxan again to find point Z in the figure. With three solutions, the trade-off curve is estimated as dashed lines “b” and “c.” Because the resulting solution had a much higher cost and lower boundary length than ConsNet’s solution, we repeated this process with line “c”, in order to find a smaller, but more fragmented solution, closer to the ConsNet solutions. This method was applied to all six scenarios.

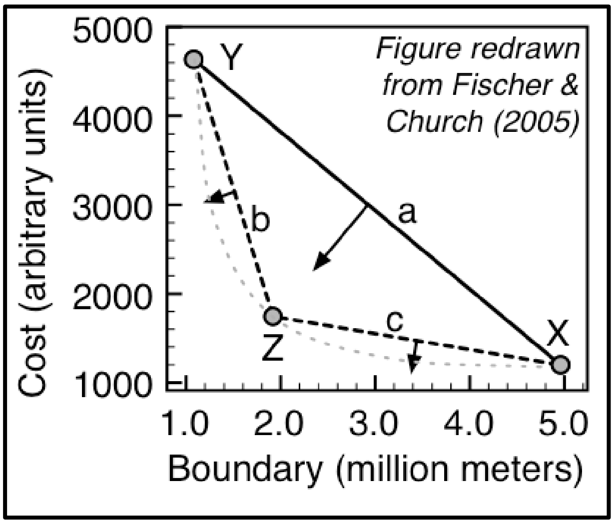

Figure 6. Available trade-off between minimizing cost and minimizing boundary length. Dotted gray line represents possible solutions on the trade-off curve. Solution X is the lowest cost solution available. Solution Y has the smallest boundary length. Solution Z achieves large reductions in boundary length for a small increase in cost (compared to X). The dashed lines "b" and "c" represent the estimated trade-off curve with three solutions "X", "Y" and "Z". Source: Ardron et al. (2010).

3.2.4.4 Input Parameter File

The Input Parameter File is used to set values for all the main parameters that control the way Marxan works. Relevant parameters of this file which were not previously discussed are described next. We used and adaptive annealing schedule, followed by two-step iterative improvement, the default type for this variable. The number of temperature decreases was left at 10 000, as recommended by the Marxan User Manual. We set the "Species missing proportion" at 0.999, or 99.9%. This is the proportion of the target a conservation feature must reach in order for it to be reported as met. This value was chosen because targets were set in the block definitions file as a proportion of the total presences. This meant some targets were decimal numbers, (e.g. 2914.25). While calibrating the SPF, we noticed some features weren't reported as meeting their targets because of these decimals. Setting the "Species missing proportion" at 0.999 solved this issue. In the example above, the species was reported as having met its target with a representation of 2914 in the reserve network. It is important to note that setting this variable does not change the way the Marxan algorithm works, it merely changes the way target achievement is reported in screen and file output. No cost threshold was used. The starting proportion of cells was set to 0, as this allowed us to assess the representation of features in the existing reserve network (because this variable doesn't affect the cells locked in or out of the solutions).

3.2.5. ConsNet

In this analysis, we used ConsNet v2.00 (Ciarleglio et al., 2009). ConsNet's metaheuristic algorithm, tabu search, tries to improve on incumbent solutions, which should preferably be generated by the inbuilt heuristic algorithms. These heuristic algorithms are very fast, so we generated starting solutions for each scenario with every algorithm, as recommend in the ConsNet manual (Ciarleglio et al., 2010). These heuristic solutions do not incorporate multiple criteria nor do they optimize a formal objective; they just serve as a starting point for a more detailed metaheuristic search.

Next we created an objective for each scenario. We used the predefined "minimize the number of cells and optimize shape" objective, as we considered this to be the most analogous to the Marxan analysis we performed. This objective tries to minimize the number of cells and looks for opportunities to improve the perimeter-to-area ratio.

3.2.5.1. Optimization

The ConsNet manual recommends running a prolonged search for each objective for at least 5*n* iterations, where *n* is the number of cells of the study area. Therefore, we started the search for each scenario from the best available heuristic solution and ran it for 300,000 iterations. This search used the "aggressive (spatial rearrangements)" neighbourhood selection strategy, which is recommended when the objective considers spatial characteristics. We then carried out an intense refinement search starting from the best solution discovered in the previous step. This refinement search ran for 50,000 iterations (Illoldi-Rangel et al., 2012) and used the "basic (use large nbhd only)" neighbourhood selection strategy. This strategy examines a large number of moves at each iteration, to make improvements that may have been missed otherwise. A refinement search is always recommended after running an extended search (Ciarleglio et al., 2010).

3.2.6. Comparisons

Results from Marxan and ConsNet were compared regarding their total area, number of clusters, average cluster area (calculated as total area divided by the number of clusters), perimeter, shape (calculated as the perimeter-to-area ratio), and total representation (i.e., the total number of occurrences summed across all conservation features). The significance of the differences was tested using the Wilcoxon signed-ranks test, using the IBM SPSS Statistics 22 software package (IBM Corp., 2013). SPSS reports a *z* score instead of the Wilcoxon *T* statistic, since the distribution of this statistic approximates a normal distribution, particularly for sample sizes of 25 and over. Because the sample size in our comparison was only 6, the reported *p*-values should be interpreted with caution.

We also calculated the proportional overlap (Carwardine et al., 2006; Prendergast et al., 1993) between the Marxan and ConsNet solutions for each scenario. The proportional overlap method normalizes the measure of overlap by the maximum possible overlap, which in this case is the lesser of the two total areas in the scenarios being compared. This is done by dividing the number of cells selected by both programs by the number of cells of the smaller solution.

3.3. Results and discussion

The reserve networks produced by Marxan and ConsNet for the six scenarios are shown in figures 7 to 12. The area selected to be added to the current protected areas network ranged from 32 km^2 (ConsNet, scenario A1) to 1934 km^2 (Marxan, scenario B3). Marxan tended to envelop existing thin and/or fragmented protected areas, such as freshwater systems, with additional reserved area. The same did not occur in ConsNet's solutions, but new selected areas were, in general, adjacent to existing areas.

The spatial attributes of the solutions are shown in Table 2 and Table 3. Reserve networks generated by Marxan had a significantly higher area than ConsNet, as well as a significantly smaller perimeter and perimeter-to-area ratio ($n = 6$, $Z = -2.201$, $p = 0.028$, for the three variables). There was no clear pattern for the number of clusters, average cluster area or total representation and no significant differences were found for these variables.

Table 2. Total area, number of clusters and average area of clusters identified by ConsNet and Marxan, for each scenario.

	Total area (km^2)		Number of clusters		Average cluster area (km^2)	
Scenarios	**ConsNet**	**Marxan**	**ConsNet**	**Marxan**	**ConsNet**	**Marxan**
A1	13250	14736	76	57	174.3	258.5
A2	14184	14245	71	61	199.8	233.5
A3	14184	14249	69	70	205.6	203.6
B1	13260	14682	81	58	163.7	253.1
B2	15076	15144	66	92	228.4	164.6
B3	15078	15152	70	85	215.4	178.3

In Marxan, there is a trade-off between the boundary length and the cost (or area) of the solutions generated (Fischer and Church, 2005; Possingham et al., 2000). This happens because Marxan incorporates boundary length in its objective function along with the cost. The trade-off is controlled by the boundary length modifier – when the BLM is increased, more emphasis is placed on minimizing the boundary relative to minimizing the cost. By carefully calibrating the BLM, one can find a BLM value for which the boundary length is substantially decreased without significantly increasing the cost. In our study, we followed a systematic approach to calibrate the BLM, suggested in the Marxan Good Practices Handbook (Ardron et al., 2010). Nevertheless, it appears Marxan was placing more emphasis in minimizing the boundary length than ConsNet.

Table 3. Perimeter, shape (perimeter-to-area ratio) and total representation of solutions produced by ConsNet and Marxan, for each scenario.

	Perimeter (km)		Shape		Total representation	
Scenarios	**ConsNet**	**Marxan**	**ConsNet**	**Marxan**	**ConsNet**	**Marxan**
A1	7888	6278	0,595	0,426	17014	18171
A2	7624	7142	0,538	0,501	19442	18515
A3	7620	7224	0,537	0,507	19399	18584
B1	7916	6344	0,597	0,432	17047	18157
B2	7788	7708	0,517	0,509	20464	20276
B3	7832	7600	0,519	0,502	20447	20316

In contrast to Marxan, ConsNet can find solutions with very different compactness for the same cost (Ciarleglio et al., 2009). This can be done by using different objectives. For example, in the first version of ConsNet, the MDS-C and the ITS objectives found a solution of equal area but very different compactness using a sample dataset with 71,248 cells and 86 conservation features (Ciarleglio et al., 2009). The MDS-C objective produced a solution with 578 clusters, compared to the 101 clusters of the ITS objective. The trade-off here is between compactness and search time: the MDS-C search took less than 10 seconds, while the ITS solution was produced in about 3 hours (however, the authors report reasonable solutions were available within 10 minutes). In the current version of ConsNet these objectives have been replaced by "minimum area" and "minimum area and shape" predefined objectives. There is also a possibility of building user-defined objectives, weighing each criterion differently. We did not choose to do this because our choice of weights might bias the comparison. Our approach used a predefined objective and can thus be easily reproduced.

The proportional overlap between solutions from ConsNet and Marxan, excluding the existing PA network, ranged from 38.7% (for scenario 1.3) to 78.6% (for scenario 2.1). However, because the added area was small relative to the existing PA network's total area, the proportional overlap of the final reserve network (i.e. including existing protected areas) was much higher, varying between 95.7% and 99.9%.

Despite the relatively low overlap between the solutions, the largest geographical areas selected by both tools when using higher targets were generally the same: in the Northeast, the area around protected areas of Serra do Xistral, and the river system of Parga, Ladra and Támoga; in the West, the areas surrounding the protected area of Baixo Miño/Minho and Serra D'Arga. These areas should be prioritized when devising an expansion plan for the current protected areas network that adequately represents the plant species considered in our study. However, if a more comprehensive conservation plan is desired, i.e., one that adequately represents the range of biodiversity found in Galicia and Northern Portugal, a multitaxonomic reserve selection approach should be adopted. Solutions generated for a single taxonomic group are inadequate for other taxonomic groups – they represent species from other taxa at lower levels than the target taxon and may even completely omit some rare species (Kremen et al., 2008). Additionally, a conservation plan developed for the entire region would likely be more efficient than two (or more) separate plans, one for Northern Portugal and another for Galicia. Kark et al. (2009) found a plan for vertebrate conservation coordinated between all countries of the Mediterranean Basin would save approximately US$67 billion, 45% of total cost, compared with a scenario where each country developed its own plan.

Consideration of costs would also be essential to planning an effective and efficient reserve network expansion. Incorporating acquisition and management costs would allow conservation goals to be achieved more efficiently and saving resources that could then be spent on other important conservation actions (Carwardine et al., 2008). The incorporation of opportunity costs would minimize the impact to other land uses, such as agriculture, forestry and extractive activities and increase the likelihood of adoption by stakeholders (Adams, Pressey, & Naidoo, 2010). Although in this study ConsNet was trying to minimize the number of cells selected, it can be set to minimize other measures of costs by using a multicriteria objective. Future research should assess the effect of incorporating non-uniform costs on the solutions produced.

Table 4. Proportional overlap between solutions produced by Marxan and ConsNet. “Selected areas” refers to the areas added to the existing reserve network. “Full reserve networks” are the solutions as reported by the programs, i.e. including the existing protected area network.

	Proportional overlap	
Scenarios	**Between selected areas** (%)	**Between full reserve networks** (%)
A1	68,8	99,9
A2	39,2	95,9
A3	38,7	95,8
B1	78,6	99,9
B2	66,8	95,9
B3	65,4	95,7

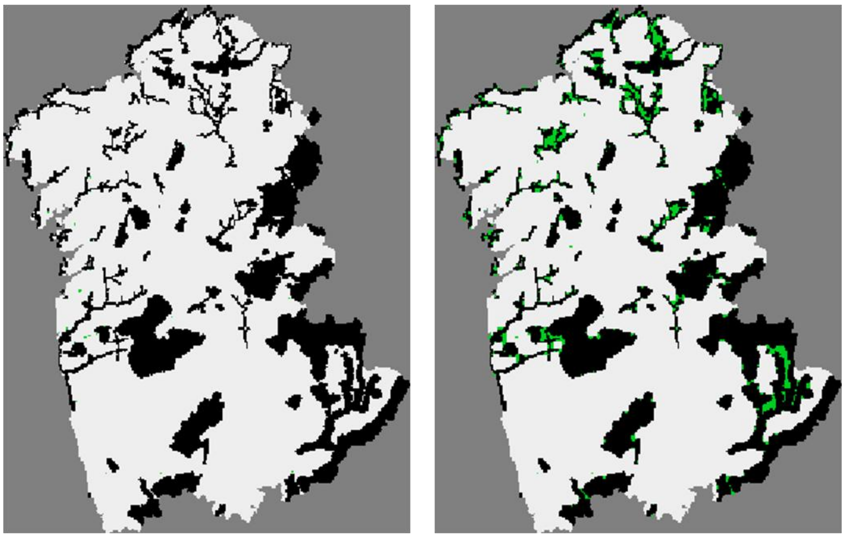

Figure 7. ConsNet (left) and Marxan (right) solutions for scenario A1. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

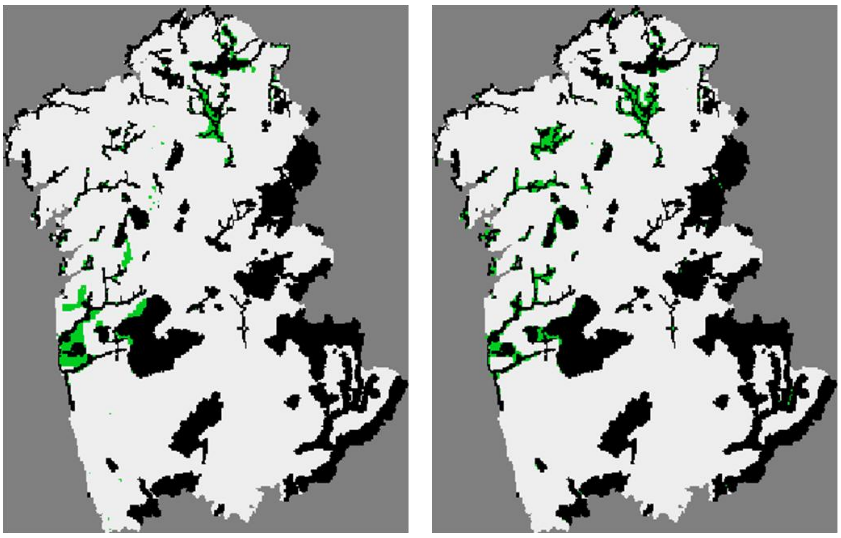

Figure 8. ConsNet (left) and Marxan (right) solutions for scenario A2. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

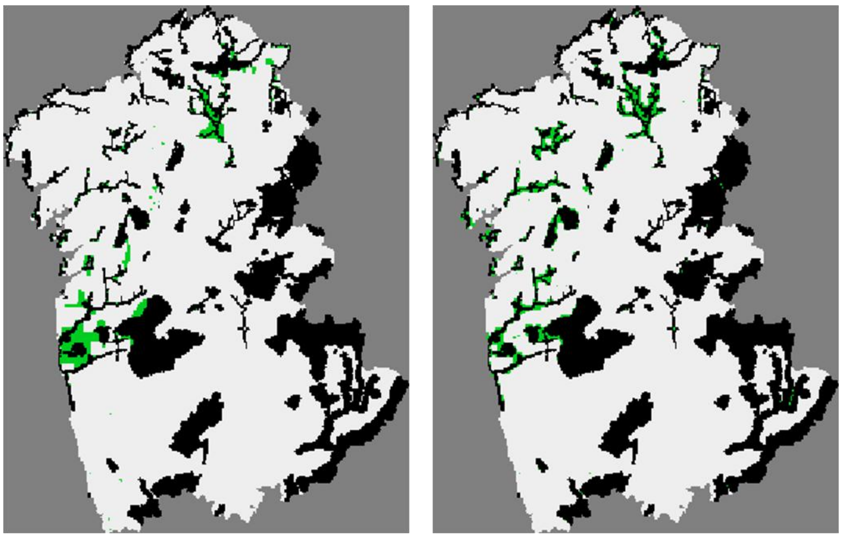

Figure 9. ConsNet (left) and Marxan (right) solutions for scenario A3. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

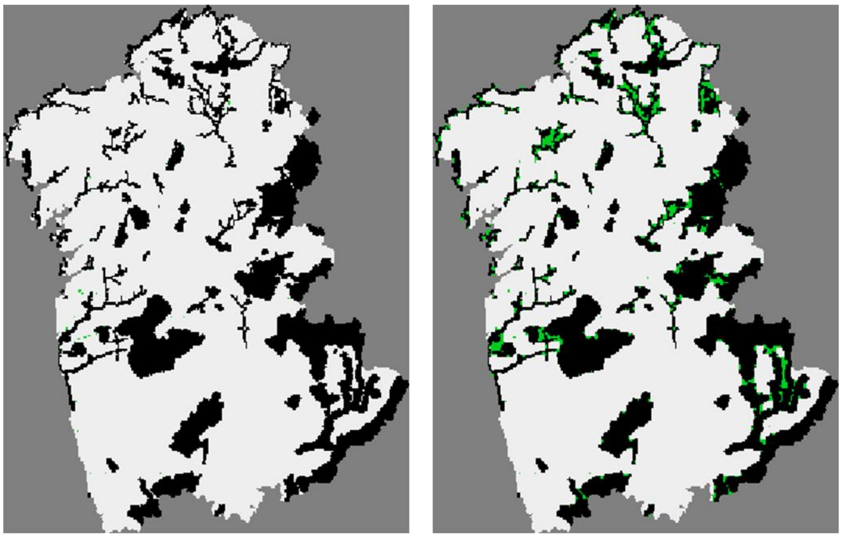

Figure 10. ConsNet (left) and Marxan (right) solutions for scenario B1. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

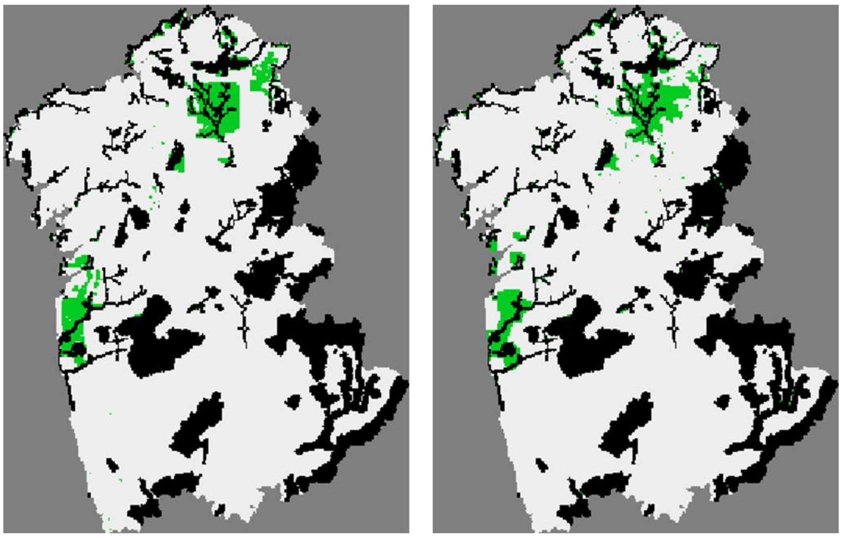

Figure 11. ConsNet (left) and Marxan (right) solutions for scenario B2. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

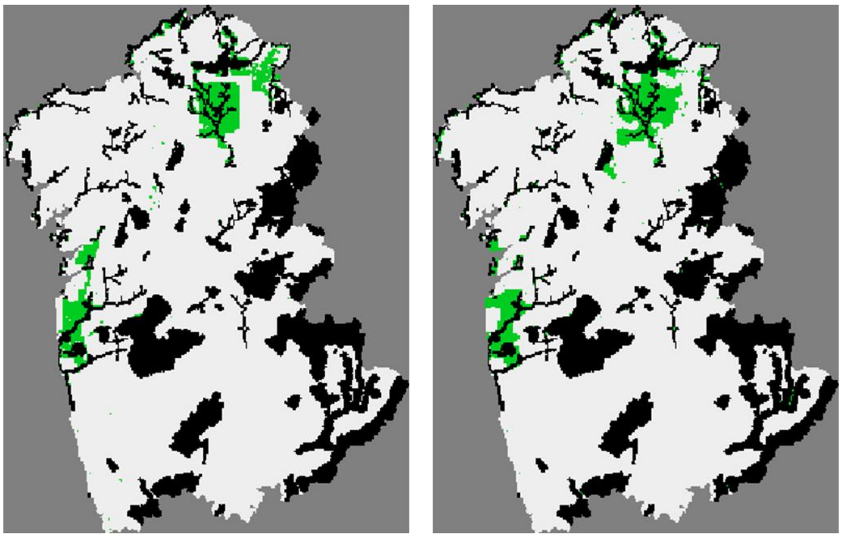

Figure 12. ConsNet (left) and Marxan (right) solutions for scenario B3. The existing reserve network is in black, while the additional area selected by the algorithms is in green.

Conclusions

To our knowledge, our study is the first to compare ConsNet and Marxan. Previous studies either compared programs that solve different problems (Allnutt et al., 2012; Delavenne et al., 2011), or programs that use heuristic algorithms with programs that use metaheuristics (Carwardine et al., 2006; Kelley et al., 2002). In this comparison, both Marxan and ConsNet were solving a spatial version of the minimum set problem. Additionally, both programs employ metaheuristic algorithms to find near-optimal solutions. Our analysis thus makes for a more exact comparison, since both tools solved a similar problem with a similar approach. Nevertheless, the algorithmic differences between Marxan and ConsNet lead to different solutions proposed. Marxan produced larger, but more compact (in terms of edge-to-area ratio) reserve networks than ConsNet.

Based on these results, we suggest using ConsNet when trying to find a minimum area solution closest to the global optimum, while incorporating multiple criteria. Marxan should be used when compactness is more important than finding a minimum area solution. Marxan is also useful when trying to improve the shape of existing reserve networks, even when no additional representation is necessary. Generating solutions with different BLM values allows the user to explore options with different levels of compactness. Another useful feature of Marxan, not yet found in ConsNet, is the summed solution output, which offers a measure of the irreplaceability of sites. This output is not adequate to find minimum set solutions, but it provides an estimate of how important sites are for achieving the defined representation targets. While a similar measure can be calculated for any number of ConsNet’s solutions using a spreadsheet, this would be a time consuming task. On the downside, Marxan requires a long and careful calibration of several parameters to find more optimal solutions. This calibration is made easier by Zonae Cogito. ConsNet has a user-friendly graphical interface, so it does not requires the use of third-party GIS software to visualize the results.

Future studies should evaluate the effects of using a larger number of conservation features, incorporating costs and using more complex multicriteria objectives, as these could change the relative performance of Marxan and ConsNet.

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