Landscape optimization in support of identifying habitat based biodiversity targets in agricultural landscapes: purpose, concepts and approaches

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1 Summary

This report provides a concise introduction, review and synthesis on the use of optimization techniques in landscape ecology. It is the purpose of this report to inform the reader about concepts, approaches and tools used for landscape optimization with particular emphasis on how these may be used in support of identifying habitat based biodiversity targets under the National Agri-environmental Standards Initiative (NAESI) in Canada. We therefore start by clarifying and defining terminology related to biodiversity, standards and targets. We discuss the principal commonalities and differences between scenario-based landscape simulation and landscape optimization and their suitability for identifying habitat based biodiversity targets. We introduce and explain the two primary approaches for optimization: Analytical and Heuristic approaches. This tutorial-like overview is followed by discussing possible optimization targets, which could be used as biodiversity standards and targets. We furthermore review available computer programs and programming libraries as well as relevant case studies. Whenever possible, we provide links to informative web sites and related literature. Preparing this report revealed a substantial body of work and literature related to optimizing schedule and spatial distribution of forest harvest, mostly in favor of maximizing harvest yields and occasionally with a conservation objective. We are aware that this report is not exhaustive but captures the conceptional essence of existing approaches. Based on this insight and confidence, we suggest to use heuristic optimization techniques in form of a customized computer program in support of identifying biodiversity targets - optimal biodiversity standards - in our case study. Further papers and reports related to this subject may be searched and downloaded for internal use @ www.elutis.com/naesi.

2 Introduction

Biodiversity has become a prominent surrogate for many concepts in ecology, such as ecosystem sustainability, stability or resilience, conservation ecology, but also an indicator for ecosystem processes with direct benefits to human kind, such as water and air quality. Biodiversity therefore represents an indicator for the state of our environment and biodiversity decline is commonly perceived as a deterioration of our biotic environmental conditions.

Biodiversity is influenced by environmental conditions and processes. Environmental conditions include landscape heterogeneity, configuration and composition of habitat for all residing species, topographical landscape characteristics and climatic conditions. Environmental processes may change environmental conditions and therefore directly or indirectly affect biodiversity. Disturbances, such as fire, floods, storms or outbreaks of pests may change or even destroy habitat for certain species. Likewise, succession may destroy and create habitat for certain species. Above all, human land-use affects both existing environmental conditions and processes with certain effects on biodiversity.

Biodiversity cannot be measured with a single variable. Various aspects of biodiversity have been described by means of established measures, such as Shannon's diversity index among many others. Still, capturing and quantifying biodiversity of a certain region in its entirety, is practically impossible. It is therefore necessary to express biodiversity by means of multiple surrogate measures. Biodiversity standards combine a set of measurable or calculable characteristics of environmental conditions. Such measurable characteristics include, among many others, species richness or habitat configuration. Calculable characteristics are derived by means of statistical or simulation models and may include population persistence or habitat suitability for a given set of species.

Biodiversity targets are based on defined biodiversity standards. Biodiversity targets therefore define a measurable state of environmental conditions. In other words, a certain biodiversity target requires particular environmental conditions and processes, which should be measurable by means of biodiversity standards.

Human land-use, such as forestry or agriculture, alters landscape heterogeneity by changing, removing (but also creating) and/or fragmenting habitat for many species. This process is commonly regarded as the main driving force for the observed changes, mostly declines, in biodiversity. Objectives of human land-use are often in direct conflict with biodiversity, simply because area is a limited resource, which can only be used once or be in one particular condition at a time (e.g. forest or field). Human dominated - cultural landscapes usually comprise a mixture of natural and managed areas. Such landscapes may still provide favorable environmental conditions for biodiversity. But these environmental conditions strongly depend on the proportion of managed vs. natural areas as well as land-use practices. In particular land-use or management practices can be adjusted or improved with respect to supporting higher biodiversity standards, which in turn may help to meet defined biodiversity targets.

What are reasonable or feasible biodiversity targets in agricultural landscapes or eco-regions? What kind of changes in management practices are necessary to achieve such biodiversity targets? How can we define and quantify biodiversity standards describing those environmental conditions, which support a certain biodiversity target? Answering these questions requires a profound understanding of how agricultural management practices affect certain environmental conditions, but also a visionary, yet realistic landscape condition, which provides the best for two conflicting targets: agricultural yield and biodiversity. This quest is essentially a call for a compromise or for an optimal landscape condition in which biodiversity is the target and human land-use the constraint.

The following sections outline and explain the origin and purpose of using landscape optimization techniques in support of identifying biodiversity targets. We will review principal approaches for solving optimization problems, case studies as well as tools in support of implementing such techniques in agricultural landscapes.

3 Landscape Optimization vs. Landscape Simulation

Landscape conditions with support for higher biodiversity standards can be identified in two principal ways. First, by means of scenario based landscape simulations. Each scenario requires a set of transition rules for certain landcover types in designated areas and their progression over time, which can be derived by mimicking natural processes, such as succession, or by mimicking and extrapolating known observed trends (e.g. urban sprawl). Each defined scenario, once simulated, will produce a landscape, whose condition must be evaluated by means of biodiversity standards. Refining and comparing the output of each simulated scenario may help in deriving landscape conditions with resulting higher biodiversity standards. As such, scenario based landscape simulations are a manual search for better landscape conditions and hence improved biodiversity standards. Although this approach allows to find better landscape conditions with respect to biodiversity standards, it is unlikely to reveal to what extent these simulated landscape conditions are the best achievable or how much better they could be.

This deficiency can be overcome by a second approach – landscape optimization. This approach essentially comprises a set of target driven, stochastic landscape simulations based on a similar set of transition rules as was used under first. The main difference is, however, that each simulated landscape condition is evaluated against a target (biodiversity standard) and is either rejected or accepted depending on whether the landscape condition improved or deteriorated compared to the previous simulation. Hence, in contrast to scenario based landscape simulations, landscape optimization may actually reveal the optimal (or near optimal) landscape condition or “compromise” under consideration of conflicting objectives: targets and constraints.

Concern has been expressed related to the realism of “optimal landscapes” and the degree of control over the optimization approach. It should be noted that landscape optimization is not a completely autonomous process, but requires and provides for user input and control. It is important to set realistic constraints and to define an appropriate objective based on which improvements are judged. Constraints may exclude polygons or entire landcover types from being changed. Furthermore, constraints may restrict or rule landcover type conversions, which is conceptionally very similar to scenario based landscape simulations. Finally, optimal landscape conditions with respect to a certain objective may just provide structural clues or “indispensable patterns” of certain landcover types, which may be captured by a set of appropriate landscape indices. Therefore it is equally important to interpret optimal landscape conditions quantitatively by means of pattern analysis and use these characteristics as benchmarks or biodiversity targets.

4 Optimization Methods

4.1 Analytical Approaches

Analytical approaches find THE optimal solution within a set of possible solutions. They are based on the assumptions of linearity, divisibility, non-negativity, independency and determinism. This means, that all considered relationships are linear, that the solution space is divisible and not negative and that all effects are independent from each other. The optimal solution is found by solving a set of linear equations, which accounts for determinism, i.e. the solution is known with certainty.

The most commonly used analytical approaches are Linear Programming (LP), Integer Programming (IP) and a mixture of both – Mixed Integer Programming (MIP). Linear programming solves a set of linear equations, which represent the objective function, decision variables and constraints. The complexity increases with the number of decision variables and constraints. LP solves linear equation systems and provides solutions for continuous decision variables. Hence the optimal solution could be a number like 5.34 for a certain decision variable. It is sometimes difficult to find the nearest optimal integer or categorical value for a corresponding decision variable, which still meets all constraints. IP and MIP have been used to address these issues.

The following depicts a very simple example for an optimization problem and its representation in LP. We assume a landscape composed of two landcover types: intensive agriculture and organic farms. Both landcover types can cover the entire landscape. Intensive agriculture has a lower estimated contribution to biodiversity than organic farming. On the other hand, intensive agriculture provides more yield than organic farming. We want to optimize the landscape for biodiversity while considering a minimum agricultural yield to be produced by the entire landscape. The question is: what proportion of both landcover types supports maximum biodiversity while still providing the required agricultural yield. This simple problem can be stated as follows:

<u>Decision variables:</u>
x1 = area of organic farming
x2 = area of intensive agricultural use

<u>Objective</u>
maximize Z = x1 (because organic farming is better for biodiversity)

<u>Constraints:</u>
x1 + x2 <= 100 (both areas must be less or equal 100% of the landscape area)
5x1 + 8x2 >= 640 (5 and 8 are yield factors per area unit, x2 provides 1.6 times (8/5) more yield than x1)

x1 and x2 >= 0 (non-negativity constraint)

Solution:

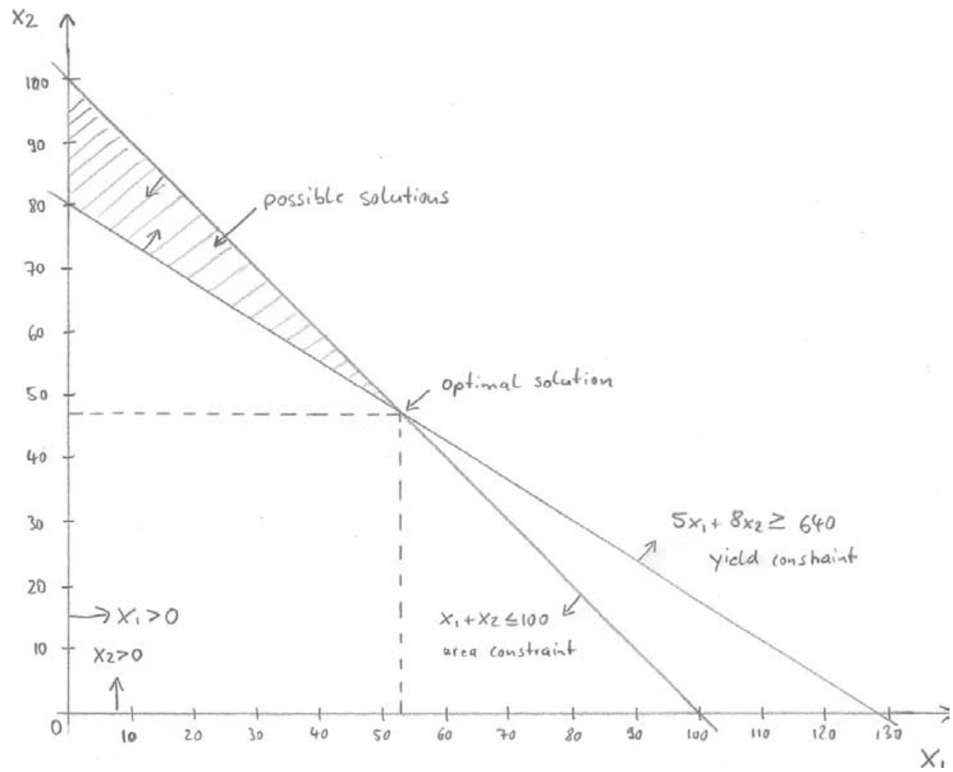

Figure 1: Graphical representation of the optimization problem. The maximum possible value for x1 is 53.33.

Linear equations:

1. x1 + x2 = 100
2. x2 = 100 – x1
3. 5x1 + 8x2 = 640
4. 5x1 + 8(100 – x1) = 640
5. 5x1 + 800 – 8x1 = 640
6. 3x1 = 160
7. x1 = 160/3 = 53.33
8. x2 = 100 – 53.33 = 46.67

Therefore the best possible solution for this problem depicts a landscape with 53.33% of organic farming and 46.67% of intensive agricultural land-use.

This simple example demonstrates the principal approach of linear programming. Real world problems are usually more complex and may involve many more decision variables, multiple objectives and many more constraints. For example, in a landscape with 100 delineated areas (polygons/patches) and 10 landcover types, there would be 100^{10} possible combinations to be explored to find an optimal solution for some objective, provided that the objective can be expressed as a linear equation. Optimization problems of this order of magnitude are therefore not suitable for analytical approaches. Furthermore, most relationships between landscape composition and configuration and the objective function are likely not linear, which may violate at least the assumption of linearity. Although this may not necessarily translate into a problem for the LP solver, the results (if obtainable) may not be correct. Alternative approaches have been adopted or developed to overcome some of these restrictions.

4.2 Heuristic Approaches

Heuristic approaches are conceptionally trial-and-error methods of problem solving. Trials usually correspond to random changes of a certain condition. If these changes result in a measurable improvement of the modified condition, than the trial was successful and becomes the base for subsequent trials. Otherwise, the trial produced an error and the corresponding inferior condition is rejected. This process is sometimes called an optimization loop or heuristic search (Figure 1). Heuristic optimization approaches will therefore produce incrementally improved conditions during the course of repeatedly executed trial-and-error, or random search runs and therefore converge toward an optimal solution (Figure 2).

The major challenge for heuristic approaches in solving optimization problems is to overcome or bypass suboptimal conditions or so called 'local optima'. Figure 4 illustrates this challenge by depicting a surface with two valleys in which a random walking, searching agent should find the lowest possible point. This agent would be programmed to move downhill, because a lower position corresponds to a better condition – the target variable for our heuristic trial-and-error methods. A step upwards corresponds to an error, while a step downwards is a success. As can be imagined, the agent searching from the left side would stop in the left valley and the corresponding result would be suboptimal, because the right valley is lower. On the other hand, if the agent would start searching from the right side, the global optimum or lowest position would be found. The success of heuristic approaches may therefore depend on the starting point of the search.

Heuristic approaches are based on random searches, which are per definition not systematic and will only incrementally explore all possible solutions. If these searches are directed toward an objective or target value, than part of the solution space may be excluded from "exploration" because of the presence of local optimal conditions. This challenge has been overcome by allowing random diversions from the principal search direction. In other words, randomly selected trials with inferior conditions may be accepted, which would correspond to allowing occasional uphill movements in Figure 4. An alternative solution would be to execute multiple search runs from different starting points to increase the likelihood of finding the global optimum.

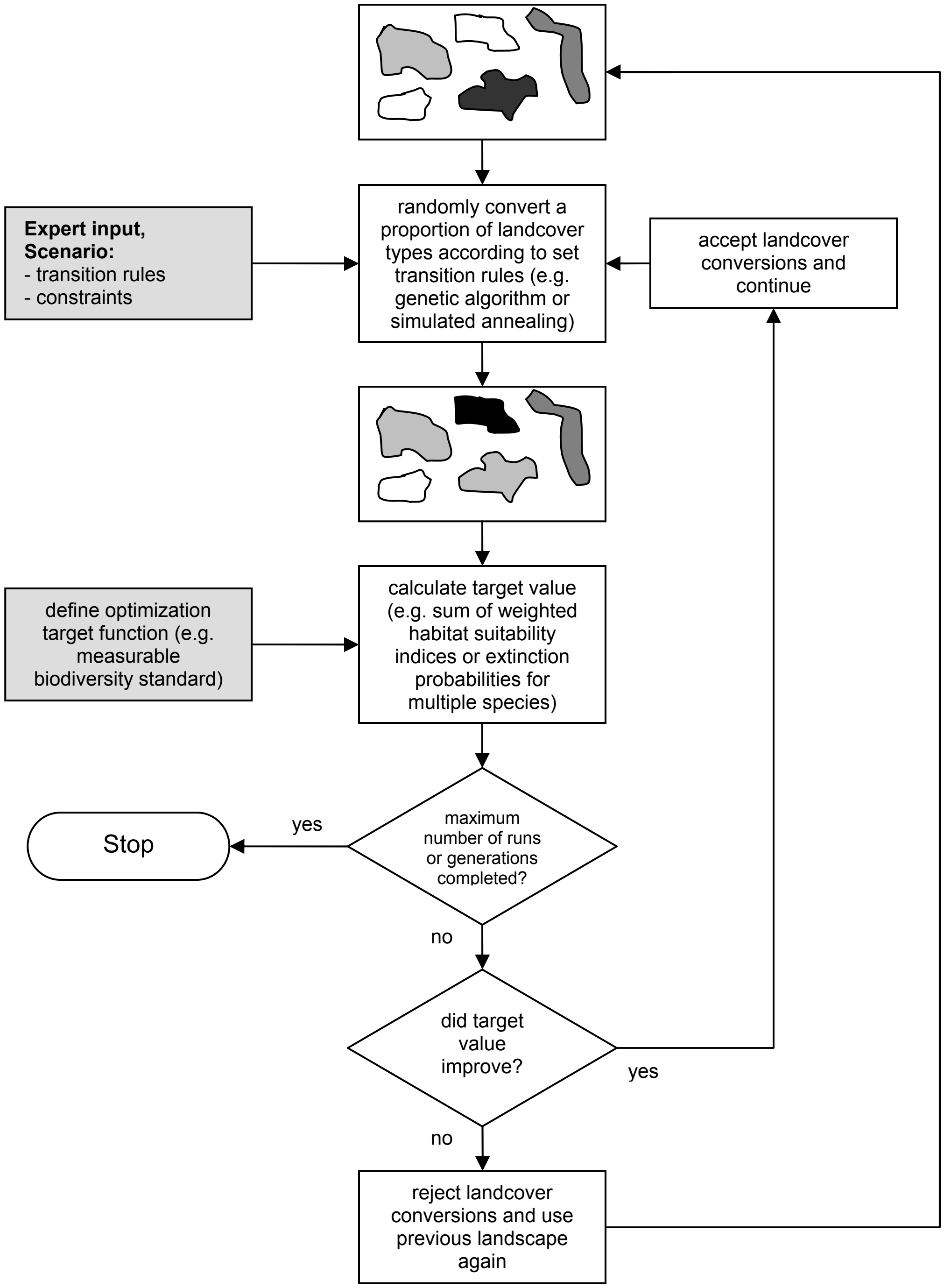

Figure 2: Principal (hill-climbing) approach for landscape optimization, based on a built-in feedback loop

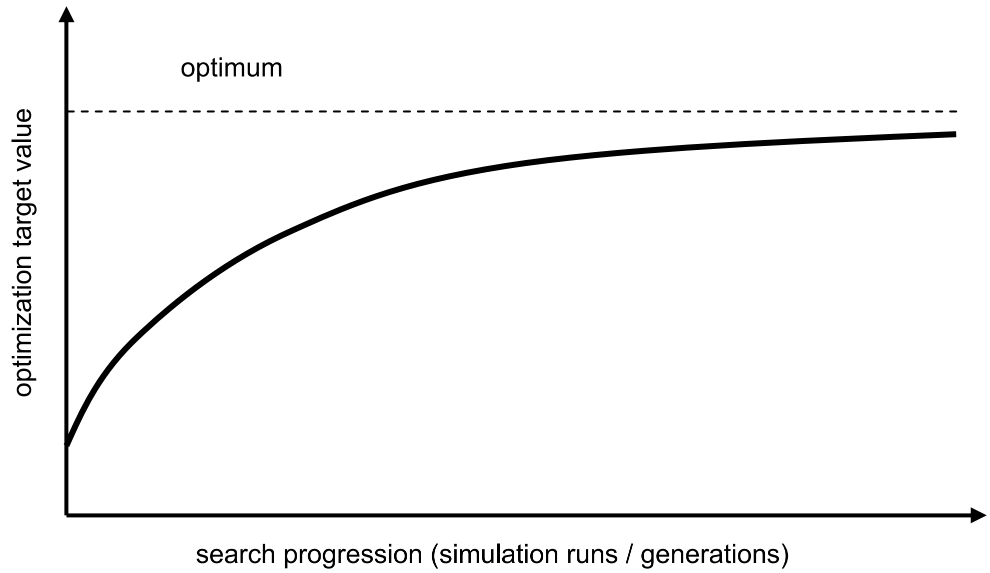

Figure 3: Principal convergence of heuristic search methods toward an optimal solution. Heuristic search methods are effective in finding near optimal solutions in very large solution spaces.

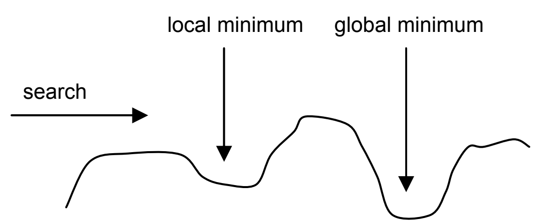

Figure 4: Example to demonstrate local and global optima and the potential of "getting stuck" in a local or suboptimal condition

4.2.1 Genetic Algorithms

Genetic algorithms (GA) mimic evolution based on the principle of "survival of the fittest". As the terminology suggests, genetic algorithms are based on crossing genomes or chromosomes. New genomes are derived by crossing two randomly chosen genomes from a population of genomes. The new genomes contain genes from both parent genomes. Survival of a new genome is determined by its "fitness", which can be determined arbitrarily. Progression of such a simulated genetic evolution is usually expressed in generations.

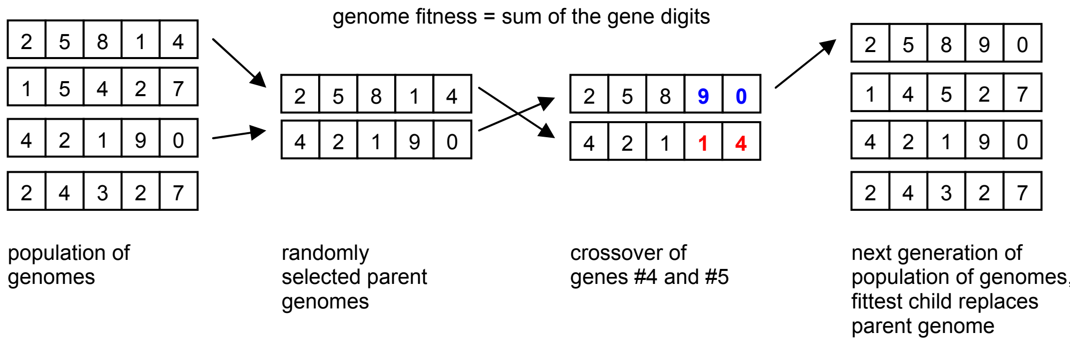

Figure 5: Example of a simple "genetic transaction". Each genome contains 5 genes. Each gene is coded by an integer value. Fitness is arbitrarily defined as the sum of all gene digits. Gene crossover is restricted to genes #4 and #5. The new child genome (2,5,8,9,0) replaces one parent, because it has a higher gene sum than its parent. Variations and extensions of this process include crossover rules, population sizes, survival rules of genomes and mutation, i.e. random changes to genes.

Application of genetic algorithms to real world problems requires to code the conditions of interest (subject to evolution and optimization) into genomes. This is perhaps the most creative and important step in utilizing genetic algorithms for the purpose of landscape optimization. A common approach is to map landcover polygons (or patches) to genes and to code landcover types as gene values. Each genome would then represent a set of changeable polygons in the landscape. A genetic transaction therefore alters the landcover types of a portion of all changeable polygons. After each genetic transaction, the new genomes can be decoded or mapped to the landscape and the "genetic fitness" of the corresponding landscapes can be determined by means of any feasible, quantitative examination. Objectives could be based on landscape composition, habitat suitability or even population viability.

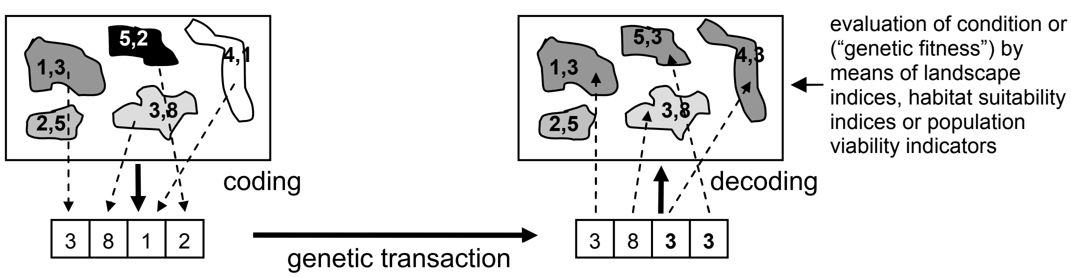

Figure 6: Example for coding a landcover map into a genome and vice versa. Note that not all polygons must be coded. Only coded polygons are eligible for change. The genetic transaction would require a population (set) of different genomes, which can be derived by coding a single landcover map into several genomes and by applying random changes to single genes (mutation).

A genetic transaction translates into a random change of landcover types of randomly selected, eligible polygons in a landcover map. The genetic algorithm is essentially a customizable simulation loop, which is governed by fitness values, generations, mutations and crossover rules. Coding and decoding landcover maps into genomes allows to project changes to the landscape, which provides the spatial context for spatially explicit evaluation rules, the values of which are fed back into the genetic algorithm.

Genetic algorithms provide a reliable random search or “trial-and-error” framework for many optimization problems. They have been applied to optimize spatio-temporal forest harvesting schedules under consideration of non-spatial (e.g. minimum age, expenses, yield flow continuity) and spatial (e.g. neighborhood dependencies) constraints. A most recent application used genetic algorithms to optimize landscapes for habitat suitability of multiple bird species (Holzkämper et al. in press). Comparisons with other heuristic methods have shown that genetic algorithms are reliable in terms of converging toward an optimal solution, but not necessarily the most efficient random search strategy (Liu et al. 2006).

4.2.2 Simulated Annealing

Simulated annealing (SA) operates on a single genome (see 4.2.1), utilizes a probabilistic and dynamic acceptance/rejection criterion and may be executed repeatedly with different starting conditions. As such, simulated annealing requires a similar coding/encoding schema as shown in Figure 6. The resulting genome, however, is changed randomly under consideration of constraining transition rules. The new genome is then decoded and evaluated against a dynamic acceptance/rejection probability. This probability decreases with increasing number of iterations and with the decrease in the relative change of the fitness value. In other words, inferior solutions are accepted with a higher probability during the beginning of the random search than toward the end of the random search. This is one mechanism to avoid or bypass local optima as explained under 4.2. In addition, a simulated annealing search may be executed multiple times with a randomly chosen starting condition at each time. This mechanism in addition to using a probabilistic acceptance/rejection criterion ensures that final solutions are near a global optimum.

Simulated annealing does not need a population of genomes, which makes this approach computationally more attractive. A comparative analysis of SA and GA (Liu et al. 2006) showed a more consistent convergence toward optimal solutions across multiple search runs for SA vs. GA. Furthermore, SA performed about ten times faster than GA. As such, simulated annealing is likely the approach of choice for complex landscape optimization problems.

5 Optimization Targets

Optimization targets or objectives - related to biodiversity in general - are quantitative characteristics of landscape conditions or measurable effects of such conditions on ecological processes. As such, the landcover map itself or the result of a simulated ecological process (e.g. dispersal or population dynamics) can be subjected to optimization targets. We will introduce a few feasible objectives in the following sections. These are, however, by far not a complete set and serve the sole purpose of stimulating imagination and to demonstrate what landscape conditions may be optimized for.

5.1 Landscape conditions

Any measurable characteristic (or combination thereof) of a landcover map can be used as optimization target. For example, landcover maps could be optimized for the amount or core areas (latter requires definition of a buffer distance) of a certain landcover type or for minimizing inter-patch distances. Such optimization targets could relate to maximizing “indispensable patterns” in landscapes with known positive effects on biodiversity.

5.2 Habitat suitability

A more sophisticated objective could be the habitat suitability index of a certain landscape for a certain species or set of species. Holzkämper et al. (in press.) used the sum of weighted habitat suitability indices for 3 bird species as optimization target. The resulting optimal landscape condition would therefore provide a configuration of landcover types optimal for the residence of individuals or breeding pairs of all 3 bird species. The weight factor could be used to prioritize one species over another based on conservation concerns. It should be noted, that landscape conditions optimized for habitat suitability indices do not consider population or metapopulation dynamics. The corresponding habitat fragmentation for single or all species may prevent viable populations. Equally the amount of certain landcover types in the optimized landscape must not necessarily support viable populations of the selected species.

5.3 Population viability

Landscape conditions affect population dynamics and therefore population viability in many different ways. Amount and fragmentation of species' habitat, but also patch sizes and shapes as well as habitat quality may have separate and/or combined effects on fecundity, survival and dispersal. Habitat amount is consistently described as one of the most important landscape characteristics for population viability. Habitat configuration becomes more important with decreasing amount of habitat. Habitat fragmentation may have negative and positive effects on population viability. Negative effects relate to landscape connectivity, while positive effects may be attributed to reducing correlation among populations. In other words, in certain circumstances habitat fragmentation may reduce the risk of simultaneous extinctions.

In order to evaluate a certain landscape condition for population viability of one or a set of species, one must run a population model such as RAMAS or ALEX. This process would require to derive one or several (if multiple species are of interest) habitat suitability maps from each generated landscape condition, create a patch map based on a defined habitat suitability threshold, project a metapopulation model to the corresponding patch map and execute the metapopulation model repeatedly. The resulting extinction risk (perhaps in combination with occupancy rates or other viability indicators) could than be used as optimization target. If multiple species are of interest, a sum of weighted extinction risks could be used to optimize the landscape condition for viability of multiple species. We are not aware of any relevant case study, although Calkin et al. 2002 attempted a single species viability optimization for various forest harvesting techniques.

Nalle et al. 2004 optimize timber production, while maximizing the geometric mean of species populations for two species with different habitat preferences. They estimate population size as a function of current and lagged habitat quality and lagged population sizes based on results from the PATCH model. Furthermore some reserve-site selection approaches incorporate the evaluation of population viability (Haight 1995, 2004; Moilanen & Cabeza 2002; Polansky et al. 2005). Most of them consider single species; only Polansky et al. 2005 use the expected number of species persisting on the landscape as the biological score for the model.

6 Tools

We evaluated a variety of computer programs, which assist in optimizing landscape related targets. We found that landscape optimization has been widely used in forest management applications. Forest management has pioneered application and adoption of optimization methods to landscape scale problems. Most of these applications focused on optimizing harvest yields across multiple planning periods under consideration of management, investment and/or proximity constraints. The output of the optimization approach is usually a strategic and/or operational management plan (i.e. a scheduled action plan or prescription on when and where to apply what harvesting method). The optimal condition is not necessarily a landscape condition, but a cost-benefit proportion or a maximized continuous yield flow across a long-term planning horizon. Tools in support of forest management planning have reached an undisputable level of sophistication, mostly with full integration of GIS technology and many reporting and visualization capabilities. With increasing recognition of forest management effects on species' habitat and biodiversity in general, such tools have been promoted and adopted to support decision making also for conservation planning. Still, it is not clear at this time as to what extent such tools can be utilized to optimize a landscape condition in favor of habitat suitability or population viability for one or multiple species. This would require to treat landscape condition as an optimization target and management plans or harvest yields as a constraint. We recognize that it would be useful to utilize many of the advanced features of modern forest planning and optimization tools, but more research and exploration is necessary to exploit their full potential and limitations with respect to the stated objective under NAESI.

We also reviewed software libraries and computer programs in support of heuristic optimization methods.

6.1 Linear Programming

6.1.1 Woodstock

Woodstock is a strategic, non-spatial forest planning tool, which supports two primary modes of operation: inventory projection (i.e. simulation of a prescribed strategic management plan) and linear programming (i.e. creation of a strategic management plan based on maximizing harvest yield). Inventory projection corresponds to simulating a set of management activities and matches the output against expected yields. This way, it can be tested whether a certain strategic management plan supports yield expectations over a certain planning horizon. Linear programming optimizes the sequence of a given set of management actions in support of maximizing yield expectations under considerations of various constraints. In other words, LP creates a strategic recipe for managing a forest while maximizing yield and meeting defined constraints. Woodstock operates around the following concepts:

1. *forest classification* schema (e.g. stands, age classes, analysis areas, development types)
2. *activities* (deterministic and probabilistic events with corresponding transition rules for the affected stand)
3. *simulator* (simulates forest growth, stage transitions)
4. *output* (age and/or time dependent yield of yield component - e.g. stand volume, basal area, site class, expenses)

As such, Woodstock allows to define and simulate or optimize a strategic forest management plan without explicit consideration of stand-level constraints, such as block sizes, proximity to recently clear-cut blocks (green-up delay).

Optimization of Woodstock based forest management plans is done with the help of external LP solvers. These are programs specialized in solving LP optimization problems as explained under 4.1. LP solvers have well defined interfaces for problem definition and solution output. A set of linear equations, constraints etc. can be expressed in standardized matrix formats. These matrices can be produced by problem specific programs, such as Woodstock. Therefore, a program like Woodstock can transform a certain management plan into a standardized LP matrix, which is then passed on to an LP solver. Likewise, the LP solver provides the solution in a similar standardized format, which can then be interpreted and visualized in Woodstock. This principal approach allows to integrate a variety of different LP solvers with Woodstock, the most prominent of which are:

- ➔ CPLEX (http://www.ilog.com/products/cplex/)
- ➔ CWHIZ (http://www.ketronms.com/cwhiz.shtml)
- ➔ LINDO & LINGO (http://www.lindo.com/)
- ➔ LPABO (http://www.orlab.org/software/lpabo/index.html)
- ➔ MOSEK (http://www.mosek.com/)
- ➔ OSL (http://www-306.ibm.com/software/data/bi/osl/)

➔ XA (http://www.sunsetsoft.com/)

6.1.2 Stanley

Stanley is a spatial and therefore operational harvest scheduling tool. Stanley simulates landscape changes by means of allocating treatments (such as cutting, planting) to polygons under consideration of stand-level constraints such as block size targets or ranges, green-up delay in adjacent or proximity areas. Similar to simulated annealing theory (see 4.2.2) Stanley searches for the optimal solution (i.e. maximize yield) by simulating random changes to treatments or by using different starting conditions over many iterative simulation runs. Each time Stanley finds a better solution, the previous one will be rejected and the search continues until the number of defined iterations is reached. Stanley is driven by the output target as provided by the strategic Woodstock management plan or action schedule.

While Woodstock optimizes the schedule and sequence of management actions in support of maximizing harvest yield, Stanley implements this strategic plan under consideration of spatial constraints and reveals, whether the strategic plan is operationally feasible. In collaboration "Woodstock and Stanley represent an hierarchical, or multiphase, approach to spatial forest planning. Rather than solving the problem in a single step, which is extraordinarily difficult – if not impossible – to do, the problem is separated into two components distinguished by the temporal and spatial resolution considered."

6.2 Heuristic Simulators

6.2.1 Programming Libraries

Name	Type	Programming Language	URL	Comment
GAlib	GA	C++	http://lancet.mit.edu/ga/	Entire library
GAUL	GA	C++	http://gaul.sourceforge.net/	Very good website with links to many GA resources
GSL	SA	C++	http://www.gnu.org/software/gsl/	Library function

Further websites:

➔ http://www.geneticprogramming.com/ga/GAsoftware.html
➔ http://www.mathtools.net/C_C__/Genetic_algorithms/
➔ http://www.cs.sandia.gov/opt/survey/sa.html

6.2.2 Computer Programs

Name	URL	Comment
Maxran	http://www.ecology.uq.edu.au/index.html?page=27710 http://www.mosaic-conservation.org/cluz/marxan_intro.html	Reserve selection tool based on simulated annealing (free)
FORPLAN	http://eco.wiz.uni-kassel.de/model_db/mdb/forplan.html	Forest optimization tool based on LP, IP, MIP
NatureServe Vista	http://www.natureserve.org/prodServices/vista/overview.jsp	Landuse Planning DSS, linked with Maxran for optimizing reserve selection (commercial)

7 Relevant Case Studies

Author	Comments
Holzkämper et al. (in press)	GA based optimization of landcover map, objective = sum of weighted habitat suitability indices for 3 bird species
Calkin et al. 2002	SA based optimization of forest harvesting schedules, objective = population persistence of Northern Flying Squirrel
Moore et al. 2000	GA based optimization of forest harvesting schedule and spatial harvest distribution, objective = abundance of birds
Nevo & Garcia 1996	Non-linear mathematical programming approach for optimizing land cover composition, objective = habitat suitability of Gadwalls, Sharp-tailed Grouse and Gray Partridge
MacMillan & Marshall 2004	LP based optimization of forest harvesting schedule, objective = habitat quality for capercailzie.

8 Suggested Approach for NAESI

We are aware of only a few case studies, which optimized landscape conditions for species specific habitat suitability or viability. All of these studies used heuristic optimization techniques. Calkin et al. 2002 used simulated annealing to optimize forest harvesting schedules for population viability of the Northern Flying Squirrel in Oregon. Holzkämper et al. in press. used genetic algorithm to optimize landscape configuration for habitat suitability of 3 bird species in Eastern Germany.

Despite the existence of sophisticated optimization tools, we found no widespread use of these tools in support of biodiversity focused landscape optimization. Article titles and brochures often suggest this type of application. However, most of these biodiversity related optimization studies merely asses the effects of optimized harvesting schedules on habitat supply for large vertebrates (e.g. Huettmann et al. 2005, Grizzly Bear Research Project in the Rocky Mountain Foothills of Alberta)

Under consideration of timing and budget constraints, but also encouraged by the 2 case studies mentioned above, we suggest to implement our suggested landscape optimization based on customized computer programs build on either GA or SA C++ libraries. A principal framework has been made available to the project team by Holzkämper et al. We will adopt the principal programming approach and customize it to the needs of this project. This approach will allow to map and quantify predicted landscape conditions.

9 References

(available for internal use under: http://www.elutis.com/naesi)

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10 Related Literature

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